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

Christine Mulhern
RAND Corporation

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

Christine Mulhern*

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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 more than cognitive or non-cognitive skill development. Counselor effectiveness is most important for low-income and low-achieving students, so 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, the labor market, and economic mobility. 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). Furthermore, the complexity associated with education decisions, such as applying to and choosing a college, is particularly burdensome for people with the lowest economic mobility and for whom these decisions may matter most - including low-income and underrepresented minority students (Dynarski et al., 2021; Chetty et al., 2020). Guidance counselors may play a valuable role in this process, but there is currently no rigorous evidence on them.

Most high schools employ guidance counselors to help students navigate complex education and labor market decisions.[1] Their role can include helping students understand the returns to education and careers, providing assistance which lowers the costs of applying to college, and recommending 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, the expansion of counselor hiring, and the Biden administration's Education Plan. The private college counseling industry is also growing rapidly, 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]

[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).

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.

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. For example, high schools with three counselors assign one counselor the beginning of the alphabet (e.g., last names A-I), another the middle (e.g., J-Q), and the third counselor the end (e.g., R-Z) based on the distribution of student names in a school and the number of counselors in the school. The exact assignment rules, including the cutoff letters and number of counselors in the school, vary across schools and over time within schools.[4]

I use these assignment rules in two ways. First, I follow the teacher literature and use the value-added model from Chetty, Friedman, and Rockoff (2014a) to estimate counselor value-added conditional on school fixed effects, cohort fixed effects and eighth grade test scores. I add in first letter of last-name fixed effects and race fixed effects to account for the assignment rules and racial/ethnic distribution across the alphabet. Second, I use the assignment rules in a coarse regression discontinuity design. For this, I examine how the relationship between student outcomes and counselor value-added varies for students with names just before or just after a counselor's assignment window relative to students with names in the counselor's assignment range.

This paper consists of five main findings.

First, I show that counselors significantly vary in their influence on high school graduation, college enrollment, selectivity, persistence, and bachelor's degrees. A one standard deviation increase in counselor effectiveness leads to a two percentage point increase in high school gradua-

There are also a growing number of non-profits providing college counseling to low-income and minority students.

[4]For instance, the rules applied to the 9th grade cohort may differ from those applied to the 10th grade cohort if the distribution of last names or size of the cohorts differ. (For most cohorts, counselor assignments are constant across their time in high school.) Figure 1 contains an example of the assignment rules.

tion and college attendance rates and significant but slightly smaller effects on college persistence and bachelor's degree completion. Counselors also impact what happens in high school - including suspensions, AP and SAT test-taking, high school course-taking, the type of college a student attends, and college majors.

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. Furthermore, individual counselors vary in terms of the types of students for whom they are most effective at improving outcomes. Some counselors have a comparative advantage for higher achieving students while others have larger effects on lower achieving students.

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 less predictive of longer-term outcomes than other short-term measures of effectiveness. Counselors' effects on college readiness and selectivity are most predictive of educational attainment, which indicates that people in schools can influence students' long-term outcomes through mechanisms other than short-term skills.[5] Counselors may increase educational attainment by providing students information about and improved access to education opportunities.

Fourth, it is challenging to predict counselor effectiveness based on observables. 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 more than other counselors. Other observable characteristics and experience, however, are not very predictive of effectiveness.

Finally, I provide evidence that the benefits, in terms of educational attainment, from improv-

[5]This paper only studies counselors specifically. However, by indicating that some people in schools can influence these outcomes, it suggests that other people, such as high school teachers, may also have these kinds of impacts.

ing 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 tend to 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.[6] Increasing access to effective counselors will also likely have effects similar to many successful college-going interventions and to increasing teacher effectiveness. Nevertheless, we do not know how to increase counselor effectiveness.

Broadly, this paper builds on three literatures. First, and most directly, it is related to research on counselors in other settings, such as colleges, job searching, housing assistance, and elementary school. This research shows that counseling can influence choices and important economic outcomes, such as job placement, college completion, earnings, and where individuals live (Card et al., 2010; Canaan, Deeb & Mouganie, forthcoming; 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 high school counselors impact students 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 &

[6]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.

Bettinger, 2021; Bettinger & Evans, 2019; Gurantz et al., 2020). The only papers to estimate the effectiveness of individual counselors do so with fewer than forty counselors and are focused on different settings (Barr & Castleman, 2021; Canaan et a;l., forthcoming). Barr & Castleman (2021) find little variation in effectiveness among counselors at an after-school program, perhaps because the counselors follow a very standardized protocol. Canaan et al., (forthcoming) find more variation in the effects of college advisors.

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., forthcoming; 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 appear to specialize in certain outcomes, but many have a comparative advantage in terms of the students they most effectively serve. In addition I find that their effects on long-term outcomes are not just through impacts on short-term skill development.

My estimates for a one standard deviation improvement in counselor effectiveness are similar in magnitude to estimates from the teacher literature on the benefits of a one standard deviation improvement in teacher effectiveness for high school completion and college outcomes. While exact comparisons between teacher and counselor effects are challenging (and not the point of this paper), the similarity in magnitude of my estimates to those for both elementary and high school teachers suggests that counselors are an important part of the education production function (Chetty, Friedman, & Rockoff, 2014b; Jackson, 2018).[7] At a high level, these comparisons suggest that improving access to effective counselors may deserve more attention in the research and policy space given the extensive resources devoted to improving teaching. There are also fewer counselors than teachers, and many counselors receive no training on college advising, so it may be easier to implement policy focused on them.

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; Altmejd et al., 2021; Mulhern, 2021). Recent work indicates that, when scaled, low-touch informational interventions have limited, if any, impacts on college enrollment (Bird et al., 2021; Gurantz et al., 2021; 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 concludes.

[7] My estimates are slightly larger than the best estimates of elementary school teachers' long-run impacts on high school completion and college attendance (Chetty, Friedman & Rockoff, 2014b; Petek & Pope, 2021) and similar in magnitude to estimates of high school teachers' effects (Jackson, 2018). These comparisons are challenging because the 9th grade teachers (from Jackson, 2018) teach many more students than counselors and elementary school teachers. Unfortunately, it is very difficult to identify the effects of 11th and 12th grade teachers and I do not have teacher data in my sample so I cannot directly compare teacher to counselor effects in Massachusetts highs schools. Furthermore, these comparisons are challenging because most estimates of teacher value-added likely understate teachers' full effects on educational attainment (Chamberlain, 2013).

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).[8] Given these responsibilities, and prior models of educators' effects, I focus on four main mechanisms through which counselors are likely to influence human capital accumulation and educational attainment. The first two mechanisms build directly on the teacher literature (e.g. Jackson, 2018) and I add a third and fourth dimension 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, 2021; 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

[8] 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, 2021).

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., 2021; Gurantz et al., 2021).[9]

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 academic achievement (Chamberlain, 2013; Jackson, 2018; Todd & Wolpin, 2003; Canaan et al., forthcoming). Existing models, however, ignore the potential effects of school personnel on long-term outcomes through mechanisms other than their influence on student academic achievement. The previous section highlights some of the ways in which counselors, in particular, can impact educational attainment without influencing student academic achievement. In this section, I expand the models typically used to show how school personnel influence educational attainment to incorporate effects on student awareness of long-term options and direct influence

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

on the barriers students face in accessing education and labor market opportunities.

I treat the first two mechanisms in section 2.1 as the academic achievement dimension. In these ways, counselors influence students' opportunities to gain both cognitive and non-cognitive skills (similar to teachers in Jackson (2018)). The third mechanism encompasses counselor effects through information, such as telling students about long-term options, their costs and benefits, and the steps needed to reach them.[10] The fourth mechanism 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.[11]

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

The quality of educator j for student i is $\omega_{ji} = D_i \omega_j$. Teacher value-added models (e.g. Jack-

[10] One could think of knowledge about career and postsecondary options as a dimension of academic achievement. 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.

[11] 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.

son, 2018) focus on educators' effects on student academic achievement, modeling student academic achievement (or ability) as $\alpha_{ij} = \nu_i + \omega_{ij} + \phi_{i-j}$ (where ϕ_{i-j} is the impact of other educators on academic achivement. Some dimensions of counselor effectiveness, however, are unrelated to student academic achievement, 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 academic achievement, similar to teachers. Following Jackson (2018), I model educators as impacting academic achievement through cognitive and non-cognitive dimensions, where $\alpha_{ij} = \nu_{ci} + \nu_{ni} + D_{ci}\omega_{cj} + D_{ni}\omega_{nj} + \phi_{i-j}$.

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 academic achievement. 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 mechanisms 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.[12] Then, $\psi_{ij} = D_{di}\omega_{dj}$.

Putting all of this together, student i's long-run outcome Y_{lij} is a function of their academic achievement, 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 academic achievement, college knowledge, and direct assistance are related to high school completion or college enrollment.

[12]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.

For example, β_l indicates how a student's academic achievement 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 their effects on each dimension, weighted by the importance 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 academic achievement 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 academic achievement 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 mechanisms other than student academic achievement.

In section 5.3 I show evidence that counselors influence educational attainment in ways that are unrelated to their effects on students' (measured) academic achievement. 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 student skills. They can also influence long-term outcomes by providing information and modifying barriers to education or career opportunities. These mechanisms of the education production function may also apply to teachers.

3 Data and Counselor Assignments

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 2019. My sample consists of the students and counselors I can link based on quasi-random last name assignment policies.

3.1 Counselors Assignments

My sample consists of students assigned to a counselor based on a last name assignment policy. These are rules for assigning high school students to a counselor based on their last name. They typically involve dividing a cohort of students among the N counselors in the school by alphabetically sorting students according to their last name and then equally dividing the alphabet across the number of counselors in the school so that each counselor has a continuous region of the alphabet and a similar number of students.

For example, if a school has three counselors and 300 incoming students, the first counselor will be assigned the first 100 last names in the alphabet, the second counselor receives the middle of the alphabet, and the third counselor receives the end. These rules are applied in two main ways. Some schools set an exact last-name cutoff so that students are exactly evenly distributed across counselors. In this example, there will be a cutoff, e.g., at Goodman, for the 100th student and then another cutoff, e.g., at Pallais, for the 200th student. Alternatively, many schools choose cutoffs that are just one or two letters for simplicity. In these cases, they allow for rounding errors in terms of how equally students are distributed across counselors. For instance, a school may choose the cutoff letter closest to the 100th student in my example, so the counselor assigned last names A-G may have 104 students and the counselor assigned H-P may have 96 students.[13]

Figure 1 shows an example of one school's assignment policies. These assignment policies vary across schools based on the number of counselors in the school and distribution of student names. They also vary across cohorts within individual schools due to the distribution of student names. For instance, Counselor One may have last names A-G for the class of 2012 but then last names A-F for the class of 2013 if there are more students at the beginning of the alphabet in the 2013 cohort. Schools typically tweak the range of letters a counselor serves for each incoming cohort according to the distribution of student names and size of the cohort. Assignment rules are, however, usually constant across time for individual cohorts (so a student's 11th grade counselor is typically the

[13] Schools appear to employ this approach for simplicity. They may be willing to forgo precise equality in caseloads given fluctuations over time in student enrollment, the relatively little time counselors spend with each individual student, and year-to-year variation in caseloads. If one counselor gets a slightly larger caseload than their peers multiple years in a row, the school may shift the assignments by one letter for a few years to even out the workloads.

same as their 12th grade counselor unless the student or counselor switches schools). Within individual schools, counselors virtually always serve the same region of the alphabet.[14] And the region they are initially assigned is usually whichever one was left open by a departing counselor.

3.2 Assignment Data

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 parents and students can easily find and contact their counselor (see Figure 1 for an example). In Massachusetts, at least a third of public high schools assigned counselors based on student last names and posted assignments on their website between 2004 and 2019. National survey data indicate that over 50% of schools assign counselors based on student last names (High School Longitudinal Study, 2009).[15]

I reviewed the archives of school counseling websites for all Massachusetts high schools between 2004 and 2019 to identify schools' assignment rules. Among Massachusetts' 393 public high schools, I identified 162 which posted a last name assignment rule on their website for at least one cohort between 2008 and 2019. 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.[16] I restrict my sample to the 146 schools which had last name assignment rules posted for at least three 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.[17] 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.

[14] 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.

[15] 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.

[16] Schools without a posted policy may have assigned counselors by a last name. Nationally, assignment by grade and random assignment are common alternatives to the name policy. Random assignment policies are rarely on websites.

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

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 (based on the consistency in assignments over time and employment records) and focus on the first counselor linked to each student.[18] Including imputed assignments increases each school's average duration in my sample to 7 cohorts. Results are very similar without the imputations (Tables A.3 and A.4).

3.3 Sample

I link 243,912 students (out of 981,428) to 761 counselors. I focus on the 224,563 students, 613 counselors, and 146 schools for which I can link counselors to at least three different cohorts with at least 20 students per cohort.[19] From this sample, I can link 578 (94%) of counselors (assigned to 218,673 students based on the counselor's name. Massachusetts provided Human Resources (HR) data on counselors' employment, education, and demographics. Table 1 describes the counselors in the HR databases and in my sample. Table 1 also describes the 20% of counselors who self-reported their education data. 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.[20] Table 2 compares the sample of students used in each section.

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 1 shows that the average counselor in my sample is matched to 218 students each year and 62 students per grade.[21] The average counselor is matched to 6 cohorts and students are matched to an average of 1.1 counselors.

Table 2 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

[18] 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.

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

[20] I use all schools with at least 0.5 FTEs for these estimates to increase my power to detect effects. I also show how results vary when using the schools in my value-added sample.

[21] 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.

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 my sample. This sample selection likely leads to underestimates of counselor effects since counselors have larger effects on low-income and low-achieving students.[22]

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 2015. 10th grade test scores and college persistence rates are not available for the 2019 cohort.[23]

3.4 Massachusetts Context

Massachusetts does not have any notable 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.[24]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

[22]Results in Table A.5 show that estimates are slightly larger when reweighted to be representative of the Massachusetts population of students and schools.

[23]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.

[24]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.

different in schools with specific college counselors or different counselor responsibilities.

4 Methods

4.1 Identifying Variation

The last name assignment policies described in section 3.1 generate observable quasi-random variation in counselor assignments that can be used to identify the causal effects of individual counselors. Counselor assignments vary based on student last names, the school a student attends, their cohort, and size of the cohort. I leverage this variation in two main ways. First, I estimate counselor value-added using the same approach Chetty, Friedman & Rockoff (2014a) use to estimate teacher effects. Second, I validate these estimates using a novel RDD-style approach.

First, I use within school variation in the counselor to which is a student is assigned based on their last name and cohort in a fixed effects model similar to those from the teacher literature (Chetty, Friedman & Rockoff, 2014a). For this, I compare outcomes for students who attend the same school but are assigned different counselors because of their last name and (or) cohort. This leverages two types of variation. First, the variation across cohorts can be seen in the Canton High School example from Figure 1 where a student with last name Daugherty would be assigned Mr. Carty if they were in the class of 2009 but Mr. Jalowayski if they were in the class of 2010. Second, I use variation in assignments due to student names. This includes variation from the Canton example where a student with the last name Kane would be assigned Mr. Jalowayski in 2009 but one with the last name King would be assigned Ms. Shapiro. I also use variation across letters, e.g., comparing a student with last name Cary to one with last name Dunn at Canton high school, conditional on average differences in C and D students (based on statewide letter fixed effects).[25]

In all my models, I include school, cohort, and first letter of last name fixed effects. School fixed effects are important because of non-random sorting to schools, and the cohort fixed effects account for secular trends.[26] The letter fixed effects subtract off statewide differences common to

[25]There is insufficient within school assignment variation to include cohort by first letter of last name fixed effects. Specification checks indicate that separately including cohort and letter fixed effects is sufficient for identification.

[26]Because of the school fixed effects my estimates do not capture information sharing or spillover effects in schools.

first letter of last name, and account for the fact that students with A last names may have higher potential outcomes than students with Z last names. I also include grade-level fixed effects to capture differences in students who enter my sample at different points.

The key identifying assumption for this approach 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, and following the teacher literature, I control for students' eighth grade test scores, demographic indicators, and indicators of services received in eighth grade.[27] As described in section 4.2, I use this approach to estimate counselor value-added following the methods from Chetty, Friedman & Rockoff (2014a). Figure 2 and Table 3 show that counselors' estimated value-added using this approach is not significantly related to students' predicted outcomes (based on their 7th grade test scores).

Second, I use the assignment rules in a regression discontinuity design. This approach leverages variation in a student's assigned counselor based on the exact letter or name where the assignment rules change. These cutoffs vary across schools and cohorts due to cohort sizes, the distribution of last names, and the number of counselors in a school. For these models, I compare students who just meet the requirements for assignment to a counselor, such as Ms. Shapiro at Canton high school, by having the last name King instead of Kane or Park instead of Prince. I use both the upper and lower bounds for the assignment rules to examine how a counselor's estimated value-added is related to the outcomes of students whose names are just before or after the assignment range relative to those within range.

4.2 Value-added Estimates

I estimate counselor-value added using the methods from Chetty, Friedman, and Rockoff (2014a). I condition on school, cohort, grade, and first letter of last name fixed effects, as well as baseline student characteristics, and allow for drift in counselor effects over time.

[27] The full set of controls includes race, gender, English learner status, receipt of services for special education, title 1 services, a 504 plan, and free or reduced price lunch, eighth grade attendance, enrollment in a Massachusetts public school in 8th grade and indicators for taking the 8th 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.

First, I compute student outcome residuals $\hat{Y}_i$ by regressing student outcomes Y_i on a vector of control variables X_i and fixed effects for student i's school δ_s, grade γ_g, cohort ψ_t, and first letter of last name ν_n. (Each student, i, is assigned to one counselor and is part of one cohort so, for simplicity, i refers to (i, j, t).) I estimate the following regression which includes counselor fixed effects in the model, so that the residuals are estimated using within counselor variation.

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

Then, I compute the student residuals as

$$\hat{Y}_i = Y_i - (\hat{\beta} X_i + \hat{\nu_n} + \hat{\delta_s} + \hat{\gamma_g} + \hat{\psi_t}) \tag{7}$$

so they include the counselor effects and a student-level error term ϵ_i. Let $\bar{Y}_{jt}$ denote the mean residual student outcome for counselor j and cohort t, so that the vector $\bar{Y}_j$ denotes the vector of mean residuals for all of a counselor's cohorts and $\bar{Y}_j^{-t}$ is the same vector but excluding cohort t.

While $\bar{Y}_{jt}$ is an unbiased estimate of a counselor's causal effect for cohort t, it is not an optimal out of sample predictor of a counselor's effectiveness. Thus, I estimate a counselor's value added as the best linear predictor of $\bar{Y}_{jt}$ based on the counselor's estimated effects in all other years $\bar{Y}_j^{-t}$. In particular, I estimate a counselor's predicted (leave-year-out) effectiveness in year t $\hat{\mu}_j$as

$$\hat{\mu}_j = \Phi \bar{Y}_j^{-t} \tag{8}$$

where Φ is the vector of coefficients obtained from regressing $\bar{Y}_t$ on $\bar{Y}_j^{-t}$.[28] Intuitively, this approach computes predicted effectiveness based on observed effects in other years and the predicted relationship between those observed measures of effectiveness and effects in year t. It accounts for drift in effectiveness over time, and will shrink noisy estimates towards the mean (of zero).

Specifically, I estimate the auto-covariance of mean residual outcomes across a counselor's cohorts. As in the teacher literature, I assume counselor value-added and student outcomes follow

[28] This is the set of coefficients that minimizes the mean-squared error of the forecasts of the residual outcomes.

a stationary process.[29] Under the stationarity assumption, $\text{Cov}(\bar{Y}_{jt}, \bar{Y}_{jt-s}) = \sigma_{Ys}$ depends only on the time lag s between the two periods. I use all of a counselor's classes (where a class is a counselor-year combination) with a time span s of up to 3 years between them to estimate σ_{Ys}.[30] Figure 3 plots the autocorrelations for my main outcomes. They are largest for the composite index of effectiveness and are quite stable over time for all estimates. Figure A.1 shows the distribution of the main value-added measures and indicates they are approximately normally distributed.

Next, I use the approach from Chetty, Friedman and Rockoff (2014a) to estimate the variance and standard deviation of counselor effects using these auto-covariances.[31] This approach takes the covariance of counselor effects over time $\sigma_{Ys} = cov(\bar{Y}_{jt}, \bar{Y}_{jt-s})$ and fits a quadratic function to the log of the covariances and extrapolates to 0 to estimate σ_{Y0}. I also report variance estimates based on the approach from Kane and Staiger (2008) which uses the covariances over one year lags σ_{Y1}. The estimates in Table 4 are very similar across these two approaches.

Finally, I estimate the relationship between counselors' value-added estimates and student outcomes. For this, I standardize the estimates of counselor value-added $\hat{\mu}_{j-t}$ using the standard deviations in Table 4 based on the Chetty, Friedman, & Rockoff (2014a) approach, so that the coefficient on the value-added estimates, ψ, can be interpreted as the impact of a one standard deviation improvement in counselor value-added.[32] Specifically, I regress student outcomes in year t, Y_i, on the leave-year-out counselor value-added measures μ_{j-t}.

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

I cluster standard errors by counselor and use the same student-level controls and fixed effects as

[29]Formally, $E[\mu_{jt}|t] = E[\epsilon_i|t] = 0$, $\text{cov}(\mu_{jt}, \mu_{j,t+s}) = \sigma_{\mu s}$, $\text{cov}(\epsilon_{it}, \epsilon_i, t+s) = \sigma_{\epsilon s}$. This means that counselor quality does not vary across cohorts, the correlation between counselor effectiveness, class shocks, and student shocks across any set of years only depends on the number of years, and the variance of counselor effects is constant across periods.

[30]Figure 3 shows that the autocorrelations are quite stable over time so the exact drift limit should not greatly impact my estimates. I do not use longer drift limits because of sample size and power limitations.

[31]Since counselors do not have multiple classes per year, I cannot use within-year variation to identify σ_μ. Thus, I use the same approach Chetty, Friedman, and Rockoff (2014a) and Kane and Staiger (2008) apply to middle school teachers to estimate the variance of their effects. This is a lower bound because it excludes some within year variation.

[32]The estimates from this approach indicate the relationship between student outcomes and assignment to a counselor who is predicted to be one standard deviation above average based on the value-added estimates. The estimates in Table 4 reflect the standard deviation of counselor effects using variation in outcomes across all of a counselor's students. While both approaches provide information about the variation in counselor effects, precisely what they estimate is slightly different.

in the construction of the value-added estimates. I also use this specification to test the relationship between counselors' short-term value-added and students' long-term outcomes.

4.3 Outcome Measures

I construct estimates of counselor effectiveness, $\hat{\mu}_j$, for a variety of high school and college outcomes. Table A.6 shows the correlations of these 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.[33]

Indices				
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 mechanisms for counselor effects described in section 2 and are similar to indices used in Petek & Pope (2021) and Jackson (2018). The college readiness and selectivity indices are related to the information and direct assistance mechanisms. 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 and is the main value-added measure I use.

[33] 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.

4.4 Validity Tests

Next, I test the validity of the value-added estimates. One may be concerned that the value-added estimates are driven by selective sorting of students to counselors based on unobserved student achievement. If students sort to counselors based on achievement, then $\text{cov}(\epsilon_i, \mu_{jt}) \neq 0$ and the counselor value-added estimates will be larger than counselors' true value-added. However, this should be less of a problem in the counselor setting than the teacher setting because we observe how students are assigned to counselors and can condition on these assignment procedures. The set of validity tests described below confirm that my value-added estimates are valid measures of counselor effects and that there is no evidence of sorting once I condition on observables.[34]

I use the main tests described in Chetty, Friedman & Rockoff (2014a) for examining forecast bias and predictive validity, as well as a regression discontinuity design to test the validity of my approach. It is important to note that my models are different from traditional test score value-added models because they cannot control for baseline measures of the same outcomes. Much of the work on test score value-added emphasizes that conditioning on baseline measures enables causal identification (e.g., Chetty, Friedman, & Rockoff, 2014a, Bacher-Hicks et al., 2017). Value-added estimates of long-run outcomes unfortunately cannot condition on baseline outcomes since there are no middle school measures of college attendance. However, other studies of long-term outcomes similarly report robustness of value-added models to using a rich set of controls such as those proposed here (e.g., Petek & Pope, 2021; Naven, 2020). Furthermore, the counselor setting is advantageous because we know how students are assigned to counselors and can condition on the assignment mechanism.[35]

First, I implement the forecast bias tests. For this, I use seventh grade test scores as a proxy for unobserved achievement and predict my main set of outcomes (e.g., college attendance) based on students' seventh grade test scores. Then I regress these predicted outcomes on counselor value-

[34] In addition, Table A.7 shows that student and counselor characteristics are not significant predictors of the number of students assigned to a counselor.

[35] This may make the selection on observables more plausible than in the teacher setting, where researchers approximate the assignment process with selection on observables. Thus, any selection bias in my estimates would need to stem from selection on observables (e.g., last name) in a way that systematically biases the results, rather than from selection on unobservables.

added. This forecast bias test provides an estimate of the proportion of variation in value-added that comes from sorting on unobserved achievement. Figure 2 and Table 3 show that counselor value-added is not significantly related to any of the predictions of the main outcomes and the point estimates in panel (A) of Table 3 are all less than 4%, indicating that selection bias is not a significant issue.[36] This is also consistent with the large literature on teachers suggesting that the selection on observables assumption is sufficient for computing unbiased estimates of teacher value-added (e.g., Chetty, Friedman & Rockoff, 2014a, Bacher-Hicks et al., 2017)

Second, one may be concerned about whether the value-added estimates are accurate out-of-sample predictors of counselor effectiveness. Following Chetty, Friedman, and Rockoff (2014a) and others, I show that the value-added estimates are strong predictors of actual student outcomes. For this, I regress residualized student outcomes on counselor value-added and report the coefficients and standard errors. Across all my value-added measures, a one standard deviation increase in counselor value-added is associated with approximately a one standard deviation increase in student outcomes. In particular, the 95% confidence intervals for my estimates of these relationships include one.[37] Figure 2 and Table 3 show these results, and Figure 2 indicates that this relationship is well approximated by the linear relationship I estimate.

Third, I implement a coarse regression discontinuity design (RDD) to examine both of these potential concerns. Overall, this presents tests very similar to the two just presented. The main idea is that a counselor's value-added should only be a good predictor of outcomes for students actually assigned to that counselor and it should not be a predictor for students whose last names are outside the assignment range. We can use the assignment rule cutoffs to study how the relationship between value-added and student outcomes changes for students with last names just before or just after the assignment range relative to students with names in the assignment range.

I fit a coarse RDD where I bin students by the distance of their last name from the assignment

[36] One of the secondary measures is a significant predictor of the predicted outcome, but the coefficient is only -3.3% and I do not focus much on the implications of this particular value-added measure. It is also negative, indicating that students who are unobservably worse may receive slightly better counselors in terms of college readiness, which would result in value-added estimates that are biased towards zero. Chetty, Friedman, and Rockoff (2014a) estimate forecast bias of 2.2% and Naven 2019 estimates forecast bias for high school value-added at 3.9% so my estimates are consistent with the literature.

[37] For nine out of ten of my main measures the 95% confidence interval includes one. The exception is the non-cognitive skills index, for which the coefficient is 0.885 and the upper bound of the 95% confidence interval is 0.96.

window for each counselor in their school. I do not have a large enough sample (or sufficient variation in assignment rules) to include bins for each letter a student is from the assignment window (e.g., 2 vs. 3 letters). Thus, I focus on students within the assignment window, those up to 6 letters before or after the threshold, and those whose names are seven or more letters before or after the threshold.[38]. For these regressions, observations are at the student by counselor level, for all counselors in a student's school. I include school by year fixed effects δ_{ts} and standard errors are clustered by student and counselor since students will have repeated observations.

$$\begin{aligned}\hat{Y}_i = InRange_{jt} \times VA_{jt} + Before_{jt} \times VA_{jt} + After_{jt} \times VA_{jt} \\ + FarBefore_{jt} \times VA_{jt} + FarAfter_{jt} \times VA_{jt} + \delta_{ts} + \epsilon_{ijt}\end{aligned}$$

Figure 4 shows that counselor value-added is a significant predictor of student outcomes for students in the assignment range but not for students before or after the letter cutoff for assignment to the counselor. Table A.8 contains the corresponding estimates.

Finally, I estimate how the forecast bias and predictive validity tests vary across different specifications for my value-added estimates. Specifically, I explore the sensitivity of these tests to using value-added estimates that control for different sets of baseline controls or fixed effects. Table A.9 shows these results. They indicate that it is important to include baseline student controls in the model, as simple school, cohort and grade fixed effects (with no demographic controls) are not enough to capture differences in students predicted outcomes across counselors. This is largely because demographic groups (e.g., Asian or Hispanic students) do not have last names that are evenly distributed across the alphabet.[39] However, once I condition on race/ethnicity and letter fixed effects, the forecast bias tests all pass and support the selection on observables assumption. This is consistent with models in the teacher value-added literature which find some sorting to teachers but that observable characteristics are sufficient to control for 99% of the bias in value-added estimates. Since I can observe precisely how students are assigned (and control for this through my fixed effects and race/ethnicity indicators) and find no evidence of sorting condi-

[38] I choose six as the cutoff because 26 letters divided into four bins is roughly 6

[39] In addition, the difference between columns (1) and (3) in Table A.9 indicates that controlling for first letter of last name and demographics is important for achieving unbiased estimates.

tional on these controls, the selection on observables assumption seems reasonable in this case. Furthermore, column 7 of Table A.9 indicates that the results are not very different if I further expand the model to include race by letter fixed effects. The estimates are also very similar when including cohort by letter fixed effects. Given the similarity across models that do and do not interact letter fixed effects with cohort or race, I focus on the simpler model because it preserves a lot more variation in outcomes and precision in my estimates.

Overall, these tests suggest that the value-added estimates are valid measures of counselor effects and that there is limited evidence of sorting.[40]

5 Counselor Effectiveness

5.1 Main Results

Figure 2 shows that students assigned to higher value-added counselors have better outcomes, including higher rates of high school graduation and college attendance. These figures are based on a counselor's predicted effectiveness, or value-added, in terms of the composite index, so they capture multiple dimensions of counselor effectiveness.[41]

Table 5 summarizes the relationship between a counselor's value-added and student outcomes. Students assigned to a counselor one standard deviation above average, in terms of value-added for the composite index, are two percentage points more likely to graduate high school and attend college. They are also 1.7 percentage points more likely to persist between a first and second year of college and 1.2 percentage points more likely to earn a bachelor's degree. Estimates are slightly larger if I instead look at counselor value-added based on the education index. For this, a one standard deviation increase in counselor value-added leads to a 2.4 percentage point increase in the probability of graduating high school, 2.5 pp for attending college, 2.2 pp for persisting between a first and second year of college, and 1.6 pp for earning a bachelor's de-

[40] Appendix C contains an additional validity test based on sibling pairs in Wake County. This shows that, on average, the difference in siblings' outcomes can be predicted by the difference in their counselors' value-added.

[41] I focus on the composite index because it captures multiple dimensions of effectiveness and contains less measurement error than the individual outcome-based measures of value-added. Most the tables report results for the composite index and outcome-based value-added measures, and the estimates are similar across measures.

gree. Counselors also influence the type of college that students attend, in terms of the college's historical graduation rate. These effects translate into one to two more students graduating high school, attending college, or earning a bachelor's degree for every standard deviation increase in counselor value-added.[42]

I also examine counselors' impacts on what students do in high school and college. Table A.10 shows that counselors influence the number and types of AP courses and tests taken. Table A.11 shows that effective counselors reduce the number of days students are absent or suspended, and they have positive impacts on high school test scores and GPAs.[43] Table A.12 also shows that they influence sat-taking, SAT scores, college match quality, and the types of colleges that students attend. And Table A.13 shows that they impact the fields in which students major. A one standard deviation improvement in counselor value-added, in terms of the composite index, is associated with a 3.5 pp increase in SAT taking, 14 point increase on the SAT (conditional on taking the test), 1.8 pp increases in the probability of attending a selective college, and attendance at a college with mean earnings $933 higher (based on the estimates from Chetty et al., 2017). Thus, the total projected impacts on mean earnings are $57,875 per cohort for a one standard deviation improvement in one counselor's value-added. Overall, these results indicate that counselor assignment can be an important determinant of students' high school and college experiences, and counselor effects on where students attend college may influence college completion, future earnings, and economic mobility (Cohodes & Goodman, 2014; Hoekstra, 2008; Chetty et al., 2017).

Panel (B) of Table 5 also shows how measures of counselor value-added based on educational attainment outcomes (e.g., value-added in terms of high school graduation or college attendance) are related to student outcomes. For instance, counselors who are one standard deviation above average in terms of high school graduation improve high school graduation rates by 2.7 percentage points. These estimates are similar to those based on the composite and education indices, and overall they indicate that value-added measures based on individual outcomes are significant

[42]Estimates of how many students are impacted come from multiplying the effect sizes in percentage points by the average number of students counselors serve per cohort (62).

[43]Counselors can be involved in suspension decisions so their effect on suspensions may be a direct effect through decision-making or an indirect effect through improving student behavior.

predictors of the relevant and related outcomes.[44] The similarity between these coefficients also indicate that, in general, counselors who are effective at increasing high school graduation are also effective at increasing college attendance and persistence.

Next, Panel (C) of Table 5 is based on the four short-term dimensions of counselor effects described in sections 2.1 and 4.3. It indicates that a one standard deviation improvement in counselor value-added in terms of the cognitive skills index is associated with a 0.057 SD increase in student outcomes on that index. Similarly, the impacts are 0.105 SD for the non-cognitive skills index, 0.058 for the college readiness index and 0.048 for the college selectivity index.

Table 4 shows the estimated variance of counselor effects. These are similar in magnitude to the estimates reported in Table 5. Estimates based on the RD design in Table 6 are also of similar magnitude.

5.2 Differences across Subgroups

Counselor effects are largest for low-achieving students.[45] Panel (A) of Figure 6 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. For nearly every measure of educational attainment, counselor effectiveness is more important for low-achieving students than high achieving students. For example, a one standard deviation improvement in counselor value-added is associated with a 3.2 pp increase in high school graduation rates and 2.5 pp increase in college attendance for low achieving students relative to 0.08pp and 1.6pp for high achieving students on those outcomes. Table 7 indicates that the outcome on which counselors have the most similar effects for students of different achievement levels is the graduation rate of the college a student attends. This may be because there is more room to change the quality of the college a high-achieving student attends than the decision of whether to attend college. Table A.14 also contains results by three levels of achievement.

[44]The estimates based on value-added for individual outcomes will typically be noisier than those based on the indices because they are based on less information.

[45]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.

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 lower achieving students (Table A.14). These results indicate that counselors may be an important resource for closing socioeconomic gaps in education.

Counselor effectiveness also matters more for low-income students than high income students, especially for high school graduation. For most other outcomes, counselor effects do not significantly vary across income groups. Table 7 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.14) 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.

Tables A.14 and A.15 also show how counselor effects vary across places and school characteristics. Effects on high school graduation are largest in urban areas and smallest in rural areas, while effects on college attendance are largest in suburban areas (though not all these differences are statistically significant). Effects on high school graduation are also larger in lower poverty and lower needs schools, while most other effects do not significantly vary across school poverty measures or school accountability levels. Furthermore, Table A.16 shows that counselors with smaller caseloads have larger impacts on high school graduation and college attendance, but differences in terms of the other outcomes are not statistically significant.[46]

I also estimate group-specific value-added to see if the distribution of counselor value-added varies across different types of students. For this, I estimate each counselor's value-added specifically for high vs. low achieving students, low-income vs. higher-income students, and white vs. non-white students (similar to Delgado, (2022)). Table A.17 shows the effects of a counselor's

[46]This does not necessarily mean that assigning counselors fewer students would lead to larger effects since caseload sizes vary with student and school characteristics.

value-added for the specific group on outcomes for that same group.[47] Nearly all of the estimates in this table are larger than the average effects reported in Table 5 so there may be benefits from matching students to counselors who are effective for students like them. This is consistent with Delgado's (2022) work which shows that teachers have comparative advantages for some types of students. Table A.18 also shows the correlation between counselors' group-specific value-added estimates across the student groups. Counselor value-added for high and low-achieving students is negatively correlated across all measures, indicating that counselors who tend to be effective for high achieving students tend to be less effective for low-achieving students, and vice versa. Conversely, counselors who are effective for white students also tend to be effective for non-white students. The correlations for value-added by income are more mixed. Overall, this indicates that matching students to counselors by achievement may improve educational attainment.

5.3 Mechanisms of Counselor Effects

Next, I explore the mechanisms through which counselors may impact long-term educational attainment. I create four indices of short-term counselor effectiveness which map to the mechanisms in section 2. The cognitive and non-cognitive skills indices map directly to the mechanisms from section 2. The cognitive skills index is based on test scores and grades in high school courses, while the non-cognitive skills index is based on attendance, suspensions, and high school dropout.

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 mechanisms. I group these outcomes into two indices: college readiness and college selectivity indices. As described in section 4, the college readiness index is based on SAT taking, SAT scores, and taking AP tests, while the college selectivity index is based on the graduation rate at the college a student attends, whether the college is selective or highly selective, and the average income of students who attended the college. Table 4 reports the variation in counselor effects on these indices and Table 3 shows that counselor effectiveness on these indices predicts the relevant outcomes.

[47] This is based on value-added on the composite index.

Figure 7 shows that counselor effects on educational attainment are primarily through impacts on college readiness and college 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 8 shows that for most outcomes, effectiveness in terms of cognitive and non-cognitive skills are not significantly related to educational attainment.[48] Furthermore, Table A.19 indicates that counselor effects on the courses students take in high school explains some of their effects on college attendance, majors, and persistence.

These results indicate that counselors' largest effects are through mechanisms other than the academic achievement 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 appear unrelated to their effects on educational attainment.[49] Counselors do, however, impact educational attainment, so their effects must be through some other mechanisms, 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.[50] 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.

[48]In a few instances, a counselor's effect on non-cognitive skills is negatively related to educational attainment. This may be due to noise since these effects are quite small, and it is important to note that these are all conditional estimates since all four value-added estimates are included in the regressions. Table 5 shows the estimates when each value-added measure is independently used in a regression.

[49]This is true for the non-cognitive skills index when I regress student outcomes on the indices one at a time in Table 5, but not for the cognitive skills index. This may be because the effectiveness dimensions that the cognitive skills index captures are correlated with those in the college readiness and selectivity dimensions.

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

5.4 Dimensions of Effectiveness

In general, good counselors tend to improve all outcomes. Most measures of effectiveness are positively and highly correlated (Table A.20). However, these simple correlations may overstate the true relationship between counselor effects on different dimensions since there is mechanical correlation between value-added measures based on the same students. Thus, I also use the leave-year-out measures of effectiveness and 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 5 shows how counselors' predicted effectiveness on various dimensions are related to student outcomes. For instance, panel (C), indicates that a one standard deviation improvement in a counselor's predicted effectiveness on the college readiness index is associated with a 1.6 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 A.2 which shows that, on average, students are more likely to attend 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 A.2 also indicates that some counselors who are good at increasing one type of educational attainment are not good at the other. This is particularly apparent when comparing effectiveness in terms of non-cognitive skills to the other dimensions. For instance, Panel (B) of Figure A.2 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 insignificant 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.

Nevertheless, most of the coefficients in Table 5 are positive and statistically significant, indicating that most counselors who are good on one dimension are also good on other dimensions. In addition, I do not find much evidence of specialization, where counselors focus only on certain outcomes or students at the expense of others (Appendix B).

5.5 Robustness Checks

Next, I show that my results are robust to alternate approaches. First, I examine the importance of the counselor assignments I imputed. Tables A.3 and A.4 show that the results are very similar when I drop observations with imputed counselor assignments. This table also explores sensitivity across the different reasons for imputation. Table A.21 also shows estimates based on a logit specification for binary outcomes, and Table A.22 shows results from the RDD specification for additional outcomes.

Second, I follow the approach from Miller, Shenhav, & Grosz (2021) to reweight my sample so that my results represent the magnitudes expected for the full population of Massachusetts public high schoolers. This approach reweights the identifying sample so that it is representative of the state's public high school population (or the state more generally) and then calculates the effect sizes for this reweighted population. These results (in Table A.5) indicate that the average effect of counselors on all Massachusetts high schoolers is likely a bit larger than my main estimates. This is probably because my sample is somewhat positively selected and I find slightly larger effects for more disadvantaged populations. For instance, the impact of a one standard deviation better counselor is associated with a 2 pp increase in graduation rates and college attendance overall vs. a 2.5 pp increase in graduation rates and 2.4pp for college attendance in the version weighted by student characteristics. These specifications are helpful for assessing the external validity of my results to the broader sample of Massachusetts high schools.

Finally, I estimate counselor value-added and a similar set of results in Wake County, North Carolina. Appendix C describes these results. Wake County is a more diverse district than Massachusetts and I find similar but slightly larger results in this location. The larger results in Wake County are consistent with the reweighted results in Table A.5 and consistent with counselors having a larger effect on lower income and lower-achieving students (which make up a larger share of the Wake County sample).

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 is related to student outcomes. I control for the first letter of the student's last name, cohort, school and assignment grade fixed effects as well as the student's academic achievement and demographics (X_i).[51]

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

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. Furthermore, these analyses are intended to be exploratory and should be interpreted with caution since many hypotheses are being tested. Nevertheless, these predictors may be useful for school administrators deciding who to hire or how to match students to counselors.

6.1 Demographics

Table 9 indicates that students are nearly 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 from a different race.[52] These effects are largest for non-white students, who are 2.8 percentage points more likely to graduate high school and 3.3 percentage points more likely to persist in college if matched to a non-white counselor. There is no detectable benefit from being matched to a counselor of the same gender (Table A.23).[53]

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

[52] 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.

[53] If anything, there may be a negative effect, but none of these estimates are statistically significant at the 5% level.

Students from underrepresented racial minority (URM) backgrounds may benefit from being matched to a counselor from a similar racial or ethnic background if these counselors have a better understanding of students' experiences and needs. For instance, counselors from these backgrounds may know more about the unique college access hurdles that URM students face and the types of colleges which are likely to be the best fit. Research on teachers also indicates that URM educators may serve as role models (Dee, 2005; Gershenson et al., forthcoming). 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.

6.2 Education

Next, I show that the undergraduate college a counselor attended is predictive of whether and where their students attend college. Data on counselors' undergraduate and graduate education are available for about 20% of the counselors in my sample.[54] 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 9 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 1.3 percentage points more likely to graduate high school than those assigned to a counselor who earned one outside of the state. There are similar effects for college attendance and the graduation rate of the college attended, but these estimates are only marginally significant. Fifty-nine percent 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

[54]Education data are self-reported. Table 1 compares these counselors to others in terms of experience and demographics. On average, they look similar to the full sample.

options, the needs of local students, or state graduation requirements than counselors educated elsewhere.[55] Receiving a master's degree in Massachusetts is also 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 (Table A.23). This is consistent with the hypothesis that local knowledge of the education system is beneficial.

I find no evidence that counselors who attended more selective undergraduate institutions are more effective than their peers, but these estimates are quite noisy. Table A.24, however, provides some evidence that counselors guide students to attend colleges which are similar to where they attended. Thus, counselors may use their own college experiences to guide the recommendations they provide to students. Table A.25 also compares the relationship between a counselor's college experience and where students attend separately for high and low achieving students.

6.3 Experience

Most measures of counselor experience are not positively related to student outcomes. Counselors with teaching licenses have students with slightly lower educational attainment (Table A.23). Thus, school administrators may not want to consider teaching experience a bonus when hiring counselors. These results may be driven by different skill requirements for teachers and counselors, or counseling may be a path selected by the least effective teachers.

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 9 indicates that the returns to experience are not positive. In particular, student outcomes are not significantly different for novice versus more experienced counselors, and high school graduation rates are lower among students assigned to counselors with more

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

years of experience. Figure 9 shows that these estimates are quite noisy, but overall there do not appear to be large returns to experience. Table A.26 also indicates that novice counselors tend to have higher value-added than more experienced counselors. This is true across multiple value-added measures. 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.

6.4 Predictors of Value-Added

Finally, I examine additional predictors of value-added. Table A.26 examines how demographics, caseloads, education, and experience relate to value-added.[56] Value-added is not significantly related to race, gender, the number of assigned students, the counselor's educational experience or years of experience. The only significant predictor is whether the counselor is a novice. Panel D of Table A.26, along with Table A.27 and Figure A.3 indicate that caseload size is not a significant predictor of the main value-added measures. However, these results are noisy, so they should be interpreted with caution.[57]

7 Comparing Counselor Effectiveness to Other Education Inputs

The evidence in the previous sections indicates 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

[56] This is different from the previous estimates which are from regressions of student outcomes on counselor characteristics. Here, I regress counselor value-added on counselor characteristics.

[57] This relationship is difficult to measure because the value-added estimates vary with the caseloads. In the empirical Bayes framework, counselors with fewer students will have their estimates shrunken more towards the mean. In addition, the number of students I measure matched to the counselor may not be their exact caseload if there is noncompliance with the assignment mechanisms or for counselors assigned to work with special populations of students.

deviation. I also show that counselor effects are similar in magnitude to some of 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 A.4 shows that 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 10 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.[58] 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.[59]

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

[58]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 in case more effective counselors are 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. Table A.28 shows the caseload estimates from table 10 for the sample of students used included the value-added estimates.

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

10 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 number of counselors over time. This approach indicates limited benefits to hiring additional counselors. Panel (C) of Figure A.4 shows a relatively flat relationship between caseloads and college attendance when caseloads vary due to the number of counselors in a school, and panel (D) of Table 10 indicates no significant relationships associated with changes in the number of counselors in a school.

Third, 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. Panel (E) of Table 10 indicates that a 100 student increase in caseloads, based on this variation, is associated with a reduction in high school graduation rates and the average graduation rates at the colleges students attend.[60]

Fourth, I 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 (D) of Figure A.4 shows that college attendance is slightly lower when caseloads are larger due to within school variation in the number of students in other grades (but this relationship is not statistically significant). However, this approach indicates a slightly larger and negative association between caseloads and high school graduation rates (1.6 pp). 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 in panels (E) and (F) of Table 10 suggest that, on average, hiring a new counselor would increase high school graduation rates by approximately 0.8 percentage points.

Table 10 also indicates that the benefits may be much larger for low-achieving students. For these students, there is a negative and statistically significant relationship between larger counselor caseloads and high school graduation, college attendance, and four-year college attendance.[61]

Finally, I do an event study around when schools hire or lose counselors. Event study plots

[60] There is also a marginally significant relationship with four-year college attendance.

[61] The same pattern is not evident for low-income students. If anything, caseloads have a more negative effect on high income students.

(Figure A.5) show only small and statistically insignificant changes in high school graduation and college attendance when an additional counselor is hired or lost. While these estimates are quite noisy, the 95% confidence intervals indicate we can rule out increases in high school graduation and college attendance that are larger than 2 percentage points when a new counselor is added or 3 percentage points when a counselor leaves. Table A.27 and Figure A.3 also describe the association between caseload size and counselor value-added.[62] Overall, there are no statistically significant relationships between caseload size and the main value-added estimates.

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.[63] 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 would increase high school graduation and four-year college attendance by about half as much as increasing counselor effectiveness by one standard deviation. However, these caseload estimates may biased upwards because they are based on variation in high school size, which impacts access to other school resources. 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. However, hiring more counselors may be much simpler than hiring more effective counselors or improving the effectiveness of existing counselors.

[62] Table A.28 shows the same specifications as Table 10 but restricted to the sample used to calculate value-added.

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

7.2 Teacher Effects

My estimates of counselor effects are similar to the best estimates of teacher effects on educational attainment. Chetty, Friedman & Rockoff (2014b) find that a one standard deviation better 3rd to 8th grade teacher, as measured by test scores, increases college attendance by 0.8 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 mechanisms other than test scores. Teachers in high school may also have larger effects on postsecondary education than elementary school teachers (Petek & Pope, 2021).

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-cognitive mechanisms, in addition to the test score channel.[64] 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. Furthermore, the 9th grade teachers in Jackson's study (and most high schools) teach several classes per year and thus may teach approximately 150 students per year. Thus, his estimates are likely lower bounds on teachers' total effects on students.

Petek & Pope (2021) also examine teachers' effects on high school outcomes and the SAT. They estimate that increasing the test-score value-added of a student's teacher by one standard deviation *each year* from grades 3 to 12 would increase SAT taking rates by 8.1 percentage points and reduce high school dropout by 0.5 percentage points. They find slightly larger benefits to focusing on improving behavior value-added, which is projected to improve SAT taking by 8.4 percentage points and high school dropout rates by 5.9 percentage points. While these estimates are larger than those I find for school counselors, they are based on improving teacher effectiveness in each grade from 3 to 12, rather than just 9-12.

While it is difficult to make precise comparisons between these types of personnel, this is not

[64] They are also based on some of the same students as the Wake County, NC counselor estimates in Appendix C.

intended to be the focus of the paper. Rather, the general magnitudes suggest that counselor effects are economically meaningful and that counselors are an important component of the education production function. This indicates that teachers are not the only important educators and counselors can have long-term effects that are similar to some types of teachers. Given the significant attention and resources devoted to teachers and improving teaching, additional attention may be warranted for counselors.

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 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., 2021; Gurantz et al., 2020; Gurantz et al., 2021; Sullivan, Castleman &

Bettinger, 2021). 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., 20121; 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, 2021). Thus, combining scalable guidance with the personalized assistance provided by school counselors may be a way to effectively reach many students.

8 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 and are an important element of the education production function.[65] They impact student behavior in high school, course-taking, high school graduation, whether and where students attend college, and persistence, majors, and degree completion in college. Counselors' impacts on educational attainment are, however, not driven by their short-term impacts on academic achievement. Rather, their effects appear to be 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. This also suggests that barriers other than a lack of cognitive and non-cognitive skills are important for educational attainment. 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, improving student behavior, and closing socioeconomic gaps in education.

Since counselors serve many students and they have impacts similar in magnitude to teachers, improving access to effective counselors may be a promising way to increase educational attainment. However, we know little about how to actually improve counselor effectiveness. Most observables are not predictive of counselor value-added, so more research is needed to determine

[65] 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).

how to identify effective counselors or improve effectiveness through training or professional development. Counselors' limited (and often nonexistent) training on college advising means that training may have important 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.

Finally, one inexpensive way to increase educational attainment could be to improve the matching of students to counselors.[66] Students benefit from assignment to counselors from the same racial group. Counselor effectiveness also matters most for low-income and low-achieving students, so it may be worth focusing on attracting the best counselors to the schools with more low-income or lower-achieving students. Furthermore, counselors vary in whether they are most effective for low or high achieving students. Matching students to counselors based on the counselor's comparative advantage and students' prior achievement (similar to how many high school courses are assigned) could be a simple way to improve educational attainment. There may, however, be negative consequences from purposeful matching if some types of students require more attention than others, or if having many students who need attention at the same time may has 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

[66] This is challenging because schools or districts need some way to identify effective counselors. Many schools now track high school and postsecondary outcomes in their student data systems or College and Career Readiness platforms like Naviance. While computing value-added is difficult, there may be value to looking at some descriptive statistics on college enrollment rates or behavioral incidents by counselor using these portals. Identifying other more practical ways for schools to measure counselor effectiveness would also be a promising area for future work.

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 people they serve.

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10 Tables and Figures

Figure 1: Example Assignment Rules

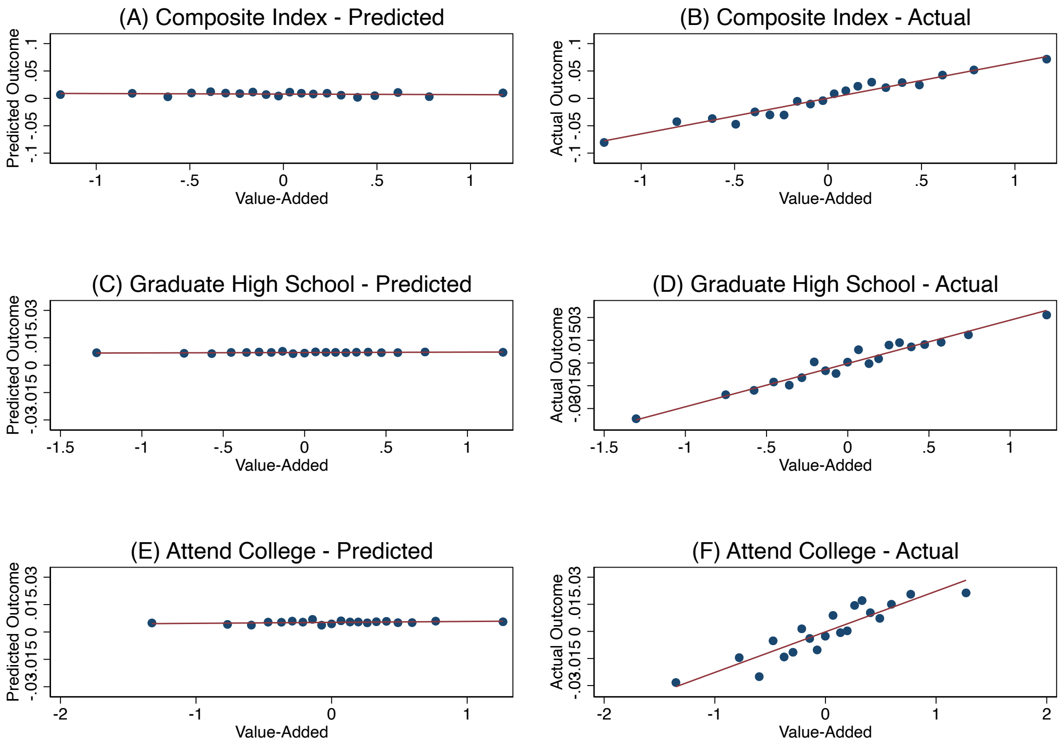
Canton High School
Guidance Department

Post High School Alternatives | Careers | Study Skills | Home

Counselor	2009	2010	2011	2012
Andrew Carty 781-821-5050 x109 cartyd@cantonma.org	A-C	A-Dr	A-C	A-Fe
Carlos Jalowayski 781-821-5050 x118 jalowayskic@cantonma.org	D-Ke	Du-Ke	D-H	Fi-Ke
Stephanie Shapiro 781-821-5050 x107 shapiros@cantonma.org	Ki-Pa	Kh-Q	J-Pe	Kl-Ra
Joanne N. Teliszewski 781-821-5050 x108 telisj@cantonma.org	Pe-Z	R-Z	Ph-Z	Re-Z

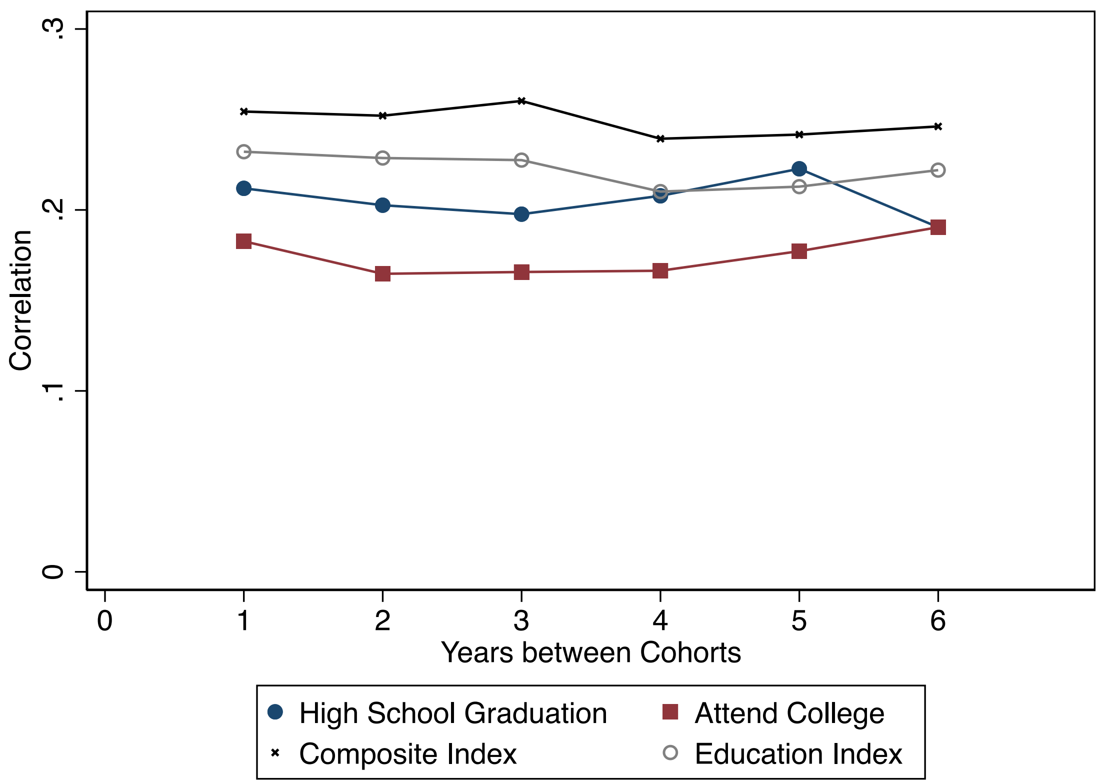
Notes: Above is an example of the assignment rules for Canton high school in 2009. The columns refer to the graduating class - e.g. 12th graders will be the graduating class of 2009 while 9th graders are the graduating class of 2012. Rules vary across these four cohorts because of changes in the distribution of student last names. In the 2012 cohort had fewer students with last names at the beginning of the alphabet, so Andrew Carty serves more letters for this cohort than the 2011 cohort. These assignment rules also vary across high schools. And variation in the number of counselors over time contributes to changes in these rules. (For example, Canton high school only had three counselors in 2005.)

Figure 2: Effects of Counselor Value-Added on Predicted and Actual Outcomes



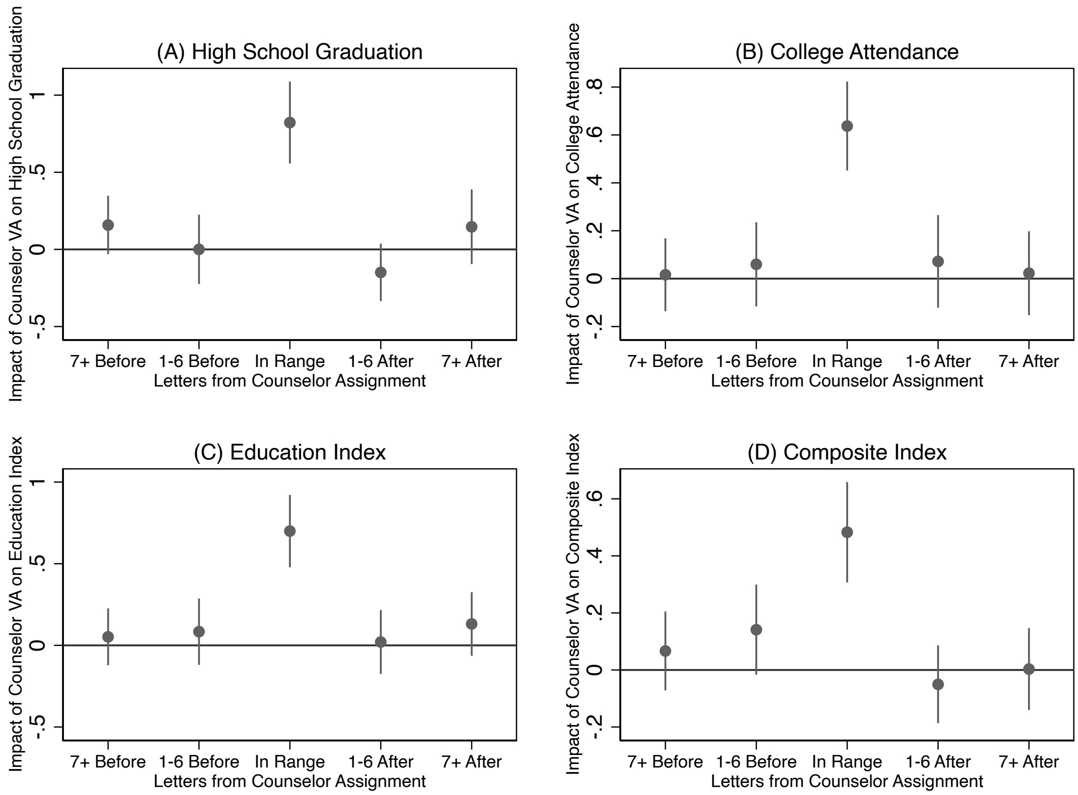
Notes: The figures above show binscatters of counselor value-added and students predicted and actual outcomes. The figures on the left show students' predicted outcomes based on their seventh grade test scores. The figures on the right show students actual outcomes. Both predicted and actual outcomes are 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. In each graph, the y-axis indicates students' predicted or actual outcome (Panels (A) and (B) are for the composite index, panels (C) and (D) for high school graduation, and panels (E) and (F) for four-year college attendance). Estimates are all The x-axis is based on counselors leave-year-out empirical Bayes estimates of effectiveness. The lines are from regressions of the residualized outcomes on counselor value-added. There are the same number of students in each bin. The relationship between counselor value-added and predicted effects is not significant at the 10% level in any of the figures on the left. Conversely, the relationship between value-added and actual outcomes is significant at the 1% level for all figures on the right, and each of the confidence interval for each of these coefficients contains 1. Table 3 contains the estimates corresponding to these figures.

Figure 3: Autocorrelation Vectors



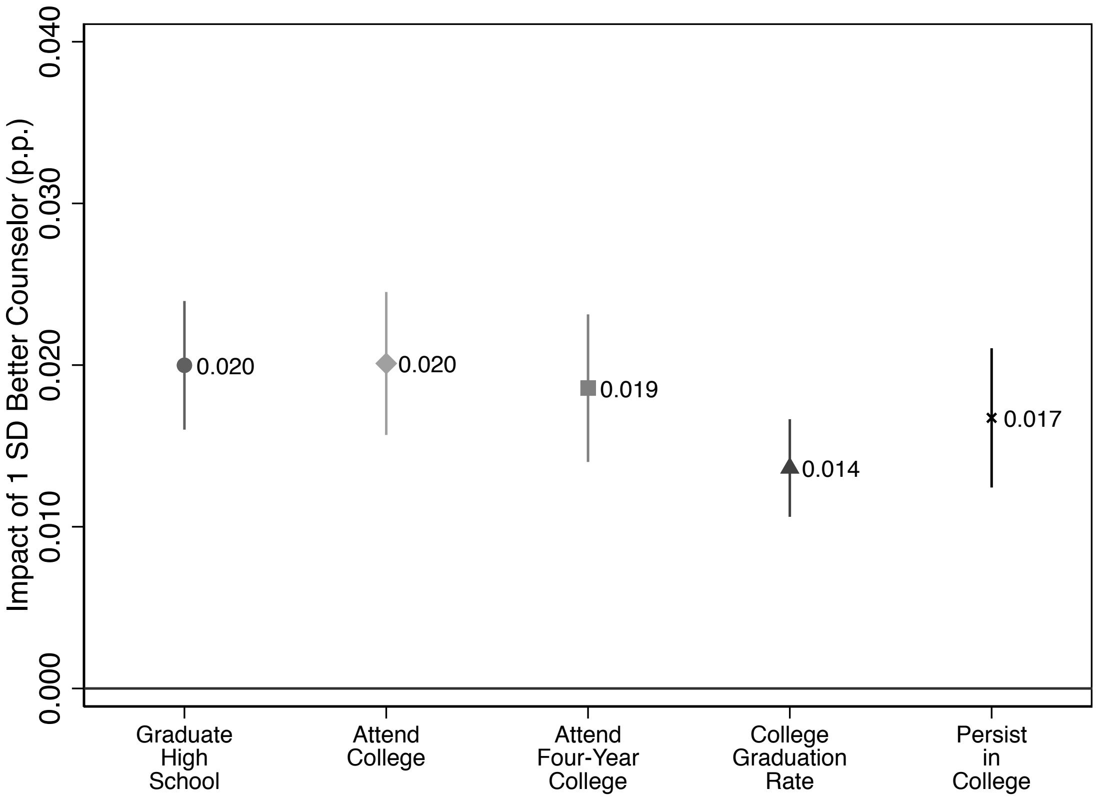
Notes: This figure shows the correlation between individual counselor residuals over time. In particular, it examines the autocorrelation for the counselor's residual effects on the Composite Index, Education Index, high school graduation and college attendance. For this, I residualize the outcomes using within-counselor variation with respect to my baseline set of controls. Then, I calculate the mean outcome for each counselor-year combination and calculate the autocorrelation coefficients as the correlation across years for each counselor.

Figure 4: Coarse Regression Discontinuity Design



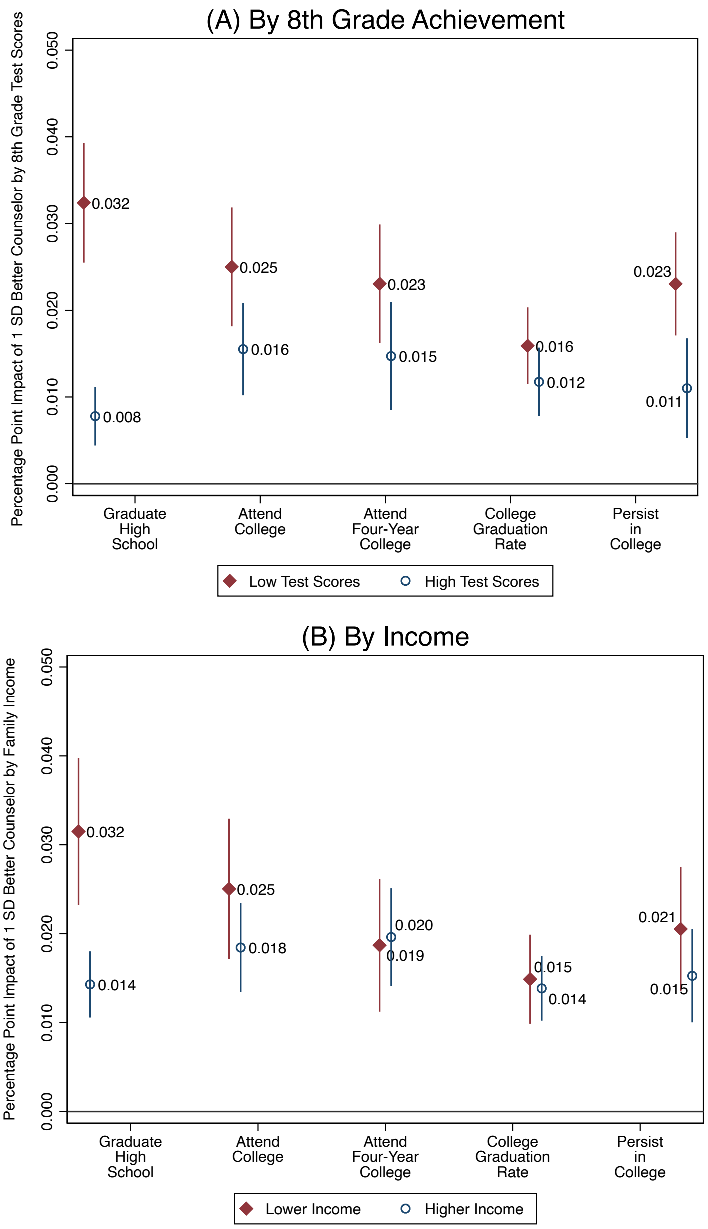
Notes: These figures show the relationship between counselor value-added (measured using the composite index) and student outcomes by students' distance (in terms of letters) to the counselor's assignment window. Since students are assigned to counselors based on the first letter(s) of their last name, I compute each student's distance (in letters) to each counselor's assignment window within each school. For instance, if Counselor Smith serves students with last names K-P, a student with last name Goodman would be 4 letters before the assignment threshold while a student with last name Walker would be 7 letters after the assignment window. A student with last name Mulhern would be assigned to this counselor and thus be "in range". Each school in my sample has multiple counselors so I compute each student's distance to each counselor in the school. The coefficients indicate that the value-added of counselors to which a student is not assigned (i.e. those outside the assignment range) is not predictive of student outcomes while value-added is predictive for students in the assignment range. The error bars represent the 95% confidence interval of my estimates. I residualize student outcomes on the main set of control variables, school, year, cohort, and first letter of last name fixed effects before regressing them on the indicators for distance to the counselor assignment windows. Because I do not have a large enough sample (or sufficient variation in assignment rules) to include bins for each letter a student is from the assignment window, I focus on students within range, those up to six letters before or after the threshold, and those whose name are more than seven letters from the threshold. (I picked six because twenty six (letters) divided into four bins is roughly six.)

Figure 5: Impact of a One Standard Deviation Improvement in Counselor Effectiveness



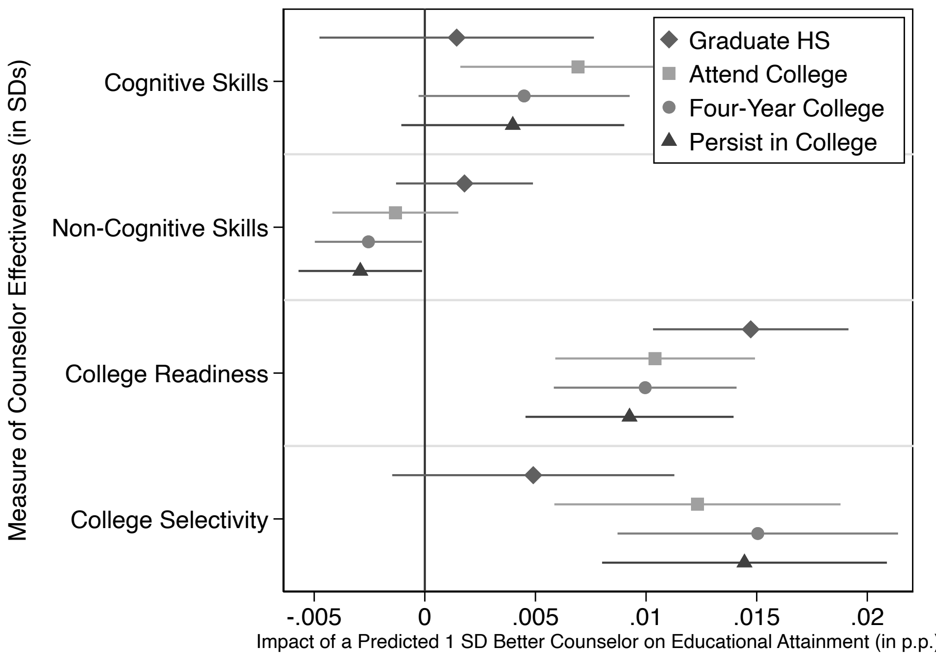
Notes: This figure shows the relationship between student outcomes and the counselor's predicted effectiveness in terms of that same outcome. The coefficients indicate the benefit of assignment to a counselor who is one standard deviation above average relative to an average counselor (as measured by impacts on students in other years). For example, the estimate furthest to the left indicates that a counselor who is one standard deviation above average in terms of high school graduation value-added increases their students' likelihood of graduating high school by 2 percentage points relative to an average counselor. 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. College enrollment is based on enrollment within six months of graduating high school. College 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 6: Impacts by Student Achievement and Family Income



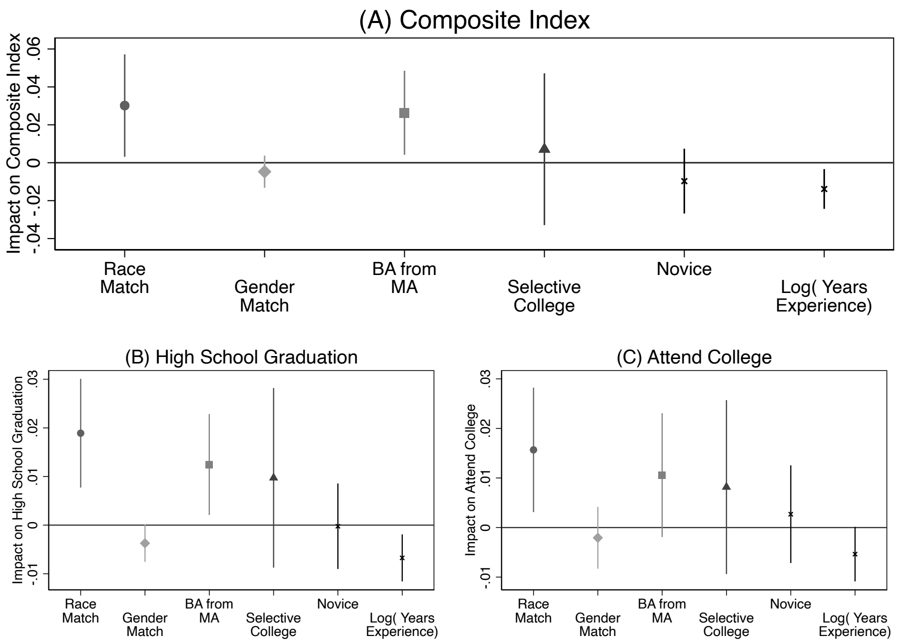
Notes: This figure shows the relationship between student outcomes and the counselor's predicted effectiveness on the composite index, separately by student type. The coefficients indicate the benefit of assignment to a counselor who is one standard deviation above average relative to an average counselor (as measured by the composite index and impacts on students in other years). The error bars represent 95% confidence intervals. Panel (A) divides students by whether their 8th grade Massachusetts test scores are above or below average. 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. (Students with missing values for the 8th grade tests are excluded from these estimates). 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.) 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. College enrollment is based on enrollment within six months of graduating high school. College graduation rate refers to the six-year graduation rate of the college a student attends. College graduation rates and persistence in college are set to zero for students who do not attend college.

Figure 7: Relationship between Short-Term measures and Long-Term Outcomes



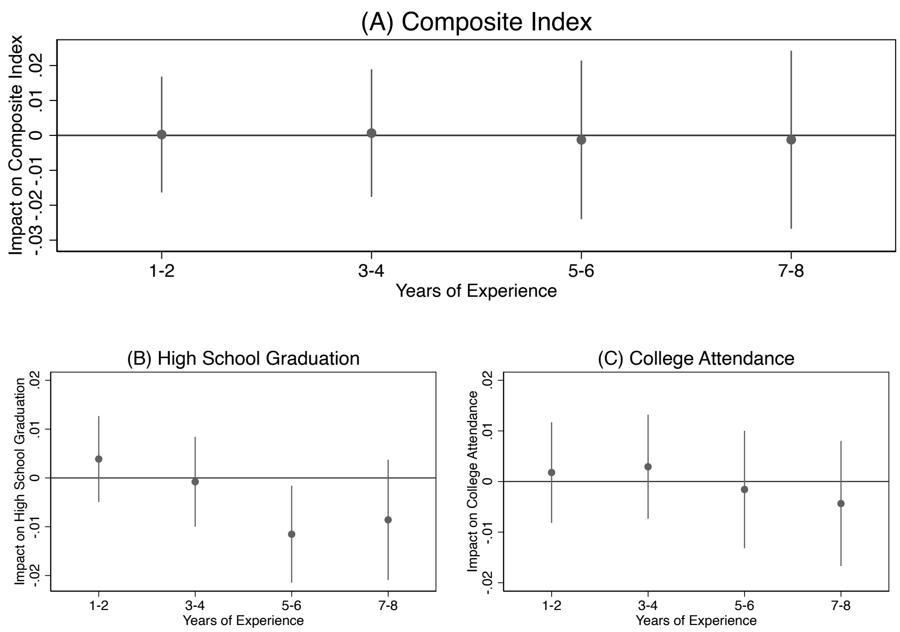
Notes: This figure shows the relationship between counselors' predicted effectiveness on four short-term dimensions of effectiveness (cognitive skills, non-cognitive skills, college readiness, and college selectivity) and students' educational attainment. The estimates are from regressions of the outcome 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 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.

Figure 8: Student Outcomes and Counselor Characteristics



Notes: These figures show the coefficients from a regression of student outcomes (the composite index of multiple outcomes, high school graduation, or college attendance) on measures of counselor characteristics - or similarities between students and counselors. Each estimate is from a separate regression and the bars represent the 95% confidence intervals. Race match is defined as assignment to a non-white counselor for non-white students and a white counselor for white students. Gender match is an indicator for assignment to a counselor whose gender is the same as the student's. BA from MA is an indicator for the counselor earning a bachelor's degree in Massachusetts. Selective college is an indicator for the counselor attending a college ranked as selective in the 2009 Barron's 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). Novice and log(years experience) are based on the counselor's years of experience as of a student's 9th grade year. The impacts on the composite index are in standard deviation units, and the effects on high school graduation and college attendance are in percentage points. College attendance is based on attendance within six months of completing high school. All estimates are from regressions which include letter of last name, school, cohort, and grade fixed effects as well as controls for students' race and gender, 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.

Figure 9: Experience and Counselor Effectiveness



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.

Table 1: Counselor Summary Statistics

	All in HR Records (1)	Assignments (2)	HR and Assignments (3)	Education Data (4)
(A) Demographics				
White	0.87	0.96	0.96	0.80
Black	0.06	0.02	0.02	0.10
Asian	0.02	0.01	0.01	0.02
Hispanic	0.04	0.01	0.01	0.06
Male	0.26	0.26	0.26	0.22
(B) Experience				
Master's	0.84	0.96	0.96	0.83
Doctorate	0.02	0.03	0.03	0.02
Supervisor	0.09	0.12	0.12	0.06
Teacher	0.21	0.15	0.15	0.19
Avg Exper	2.72	4.30	4.30	2.72
Switch in MA	0.27	0.25	0.25	0.30
(C) Counselor Assignments				
Students Matched to Counselor	270	342	355	301
Students Matched per Cohort	57	62	62	56
Students Matched per Year	215	218	217	219
Counselor Years in Sample	5.1	6.1	6.3	5.0
Counselors	3,335	613	578	122

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

Table 2: Student Summary Statistics

	All	Match to Counselor			Caseload Sample
		VA Sample	In HR Sample	Ed Sample	
	(1)	(2)	(3)	(4)	(5)
(A) Demographics					
White	0.67	0.79	0.79	0.75	0.70
Asian	0.06	0.05	0.05	0.04	0.06
Black	0.10	0.05	0.05	0.07	0.09
Hispanic	0.16	0.09	0.09	0.13	0.15
Limited English	0.19	0.06	0.06	0.13	0.18
Special Ed	0.20	0.18	0.18	0.18	0.18
Free/Reduced Lunch	0.42	0.32	0.32	0.37	0.41
Grade 8 Test	-0.00	0.16	0.16	0.11	0.04
(B) HS Academics					
Days Truant	8.35	8.78	8.90	12.95	8.87
Suspended	0.16	0.11	0.11	0.10	0.15
Took AP Test	0.29	0.39	0.39	0.40	0.34
GPA	2.66	2.80	2.80	2.76	2.68
Took SAT	0.52	0.64	0.64	0.66	0.60
SAT Score	1049	1082	1082	1075	1055
Graduate High School	0.78	0.87	0.87	0.86	0.82
(C) College Outcomes					
Attend College	0.56	0.66	0.66	0.66	0.60
Four-Year College	0.43	0.53	0.53	0.53	0.46
Highly Selective	0.09	0.12	0.12	0.12	0.10
Persist 1st Year	0.47	0.56	0.56	0.56	0.50
Earn BA	0.32	0.41	0.41	0.41	0.35
(D) Counselor Assignments					
Number of Counselors		1.12	1.11	1.12	
N	981,428	224,563	218,673	55,161	806,689

Notes: Column 1 contains all students in a MA high school who were projected to graduate between 2008 and 2019. Column 2 contains all students in column 1 who were matched to a counselor with students in at least three different cohorts (of at least 20 students). This is the sample used for the main effectiveness estimates. Column 3 contains all students from column 2 whose counselor can be matched to a record in the Human Resources Database. Column 4 contains all students who were matched to counselor with a record in the Human Resources Database who also self-reported their education. Column 5 contains all students in column 1 who were enrolled in a school in a year with a valid measure of full-time equivalent counselors. This means there were at least .5 FTEs in the school and the caseloads were computed to be between 100 and 500 students. I apply this restriction to ensure that the caseload estimates are not biased by outliers due to errors in the data. Limited English is an indicator for whether the student was an English language learner in high school. Special Ed is an indicator for whether the student ever received special education services in a public Massachusetts high school. Free/Reduced lunch is an indicator for whether the student received free or reduced-price lunch in high school. Days truant refers to the number of unexcused absences a student has in high school. GPA data are not available for all years. GPAs are on a four-point scale and are computed based on reported grades in core courses. SATs are on the 2400 scale. Attend college is an indicator for whether the student attended college within six months of graduating high school. Highly selective is an indicator for attending a highly selective college as classified by Barron's rankings in 2009. Persist 1st Year is an indicator for whether a student persists between their first and second years of college. BA is an indicator for earning a Bachelor' degree within five years of starting college. All remaining outcomes represent the fraction of students in the sample achieving that outcome.

Table 3: Validity of Predicted Effects

	Predicted Outcome (1)	Actual Outcome (2)
VA Measure		
High School Graduation	0.008	1.112***
	(0.005)	(0.111)
Attend College	0.021	0.908***
	(0.013)	(0.086)
Four-year College	-0.006	1.002***
	(0.022)	(0.159)
Bachelor's Degree	-0.016	1.002**
	(0.049)	(0.420)
Composite Index	-0.018	1.155***
	(0.021)	(0.086)
Non-Cognitive Skills	-0.002	0.885***
	(0.001)	(0.038)
Cognitive Skills	0.038	1.255***
	(0.053)	(0.154)
College Readiness	-0.032***	1.037***
	(0.011)	(0.091)
College Selectivity	0.023	1.136***
	(0.029)	(0.161)
Education Attainment Index	0.007	1.114***
	(0.014)	(0.098)
N	198,185	224,563

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). Each estimate comes from a regression of a student's predicted or actual (residual) outcome on their counselor's leave-one-out value-added estimate for the relevant outcome. In all cases, I use the residual outcome, controlling for the first letter of a student's last name, school, grade, and year (when a student was first assigned to the counselor), 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 column (1) the outcome is the student's predicted outcome (e.g. high school graduation) based on their seventh grade test scores. In column (2), the dependent variable is the student's actual outcome (e.g. high school graduation). 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.

Table 4: Standard Deviations of Counselor Effects

	All Controls		Letter, Cohort, School FE		No Controls	
	Covariance Approach (1)	CFR Approach (2)	Covariance Approach (3)	CFR Approach (4)	Covariance Approach (5)	CFR Approach (6)
Composite Index	0.059	0.056	0.095	0.090	0.444	0.446
Education Index	0.063	0.056	0.102	0.095	0.323	0.328
High School Graduation	0.028	0.026	0.041	0.038	0.084	0.084
College Attendance	0.027	0.025	0.043	0.040	0.136	0.138
Four-Year College Attendance	0.025	0.022	0.041	0.037	0.187	0.190
College's Graduation Rate	0.016	0.015	0.027	0.026	0.162	0.163
Persistence in College	0.025	0.023	0.045	0.042	0.150	0.152
Cognitive Skills	0.046	0.046	0.082	0.079	0.422	0.425
Non-Cognitive Skills	0.113	0.119	0.114	0.119	0.309	0.317
College Readiness	0.084	0.083	0.109	0.105	0.347	0.351
College Quality	0.047	0.044	0.076	0.072	0.464	0.462

Notes: Columns 1, 3 and 5 show estimates of the standard deviation of counselor effects based on the covariance of individual counselor effects over time. Columns 2, 4 and 6 show estimates based on the approach for computing the variance of teacher (or counselor) effects in Chetty, Friedman and Rockoff (2014a). The first two columns show the estimates based on the full set of controls used to compute the value-added estimates. This includes 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), 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. Columns 3 and 4 only include school fixed effects, first letter of last name fixed effects, grade fixed effects and cohort fixed effects. Columns 5 and 6 include no controls (of fixed effects).

Table 5: Measures of Predicted Effectiveness and Student Outcomes

	Student Outcomes						Indices			
	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Bachelor's Degree (6)	Cognitive Skills (7)	Non-Cognitive Skills (8)	College Readiness (9)	College Selectivity (10)
(A) Effectiveness for Overall Indices										
Composite Index	0.020***	0.020***	0.019***	0.014***	0.017***	0.012***	0.019***	0.069***	0.071***	0.037***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.009)	(0.007)	(0.005)
Education Index	0.024***	0.025***	0.020***	0.014***	0.022***	0.016***	0.023***	0.010	0.057***	0.039***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.009)	(0.006)	(0.005)
(B) Effectiveness for Education										
Graduate High School	0.027***	0.022***	0.014***	0.010***	0.017***	0.014***	0.013**	0.026***	0.057***	0.027***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.010)	(0.006)	(0.004)
Attend College	0.026***	0.021***	0.014***	0.010***	0.016***	0.013***	0.013**	0.025***	0.055***	0.026***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.010)	(0.006)	(0.004)
Attend Four-Year	0.014***	0.020***	0.020***	0.014***	0.020***	0.013***	0.022***	-0.006	0.051***	0.041***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.010)	(0.008)	(0.006)
Graduation Rate	0.013***	0.017***	0.019***	0.014***	0.017***	0.012***	0.015***	0.005	0.058***	0.041***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.010)	(0.008)	(0.006)
Persist 1st Year	0.019***	0.024***	0.019***	0.012***	0.020***	0.014***	0.022***	-0.006	0.040***	0.038***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)	(0.010)	(0.008)	(0.005)
Bachelor's Degree	0.021***	0.022***	0.017***	0.011***	0.018***	0.010*	0.008	0.023	0.032**	0.029***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.006)	(0.009)	(0.017)	(0.013)	(0.009)
(C) Effectiveness for SR Indices										
Cognitive Skills	0.007**	0.014***	0.013***	0.007***	0.012***	0.004	0.057***	-0.037***	0.012	0.027***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)	(0.012)	(0.008)	(0.005)
Non-Cognitive Skills	0.004**	-0.000	-0.001	0.000	-0.002	0.001	-0.013***	0.105***	0.020***	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.003)
College Readiness	0.016***	0.013***	0.013***	0.011***	0.012***	0.008***	0.000	0.042***	0.068***	0.026***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(0.008)	(0.007)	(0.004)
College Quality	0.014***	0.021***	0.023***	0.017***	0.021***	0.012***	0.028***	-0.005	0.059***	0.048***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)	(0.010)	(0.008)	(0.007)
N	224,563	224,563	224,563	224,563	201,834	128,542	224,563	224,563	224,563	224,563

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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.

Table 6: Regression Discontinuity Estimates of Counselor Effects by Letters to Assignment Ranges

	Graduate High School (1)	Attend College (2)	Four-Year College (3)	Graduation Rate (4)	Persist 1st Year (5)	Cognitive Skills (6)	Non-Cognitive Skills (7)	College Readiness (8)	College Selectivity (9)
(A) Composite VA									
7+ Before	0.004**	0.001	0.001	0.001	0.004	0.000	0.003	0.007	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
1-6 Before	-0.001	0.003	0.005*	0.003*	0.004	0.006*	-0.001	0.007	0.011**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)
In Range	0.016***	0.013***	0.010***	0.005***	0.012***	0.012***	0.009**	0.034***	0.016***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
1-6 After	-0.002	0.002	0.002	-0.000	0.002	-0.003	-0.007	-0.000	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
7+ After	0.002	0.002	-0.003	-0.001	-0.003	0.001	-0.005	0.000	0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
(B) Outcome-specific VA									
7+ Before	0.004	0.000	-0.000	0.001	0.001	0.001	0.006**	0.013***	-0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)	(0.007)
1-6 Before	0.000	0.001	0.005	0.003	0.000	0.005	0.000	0.014**	0.007
	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)	(0.006)	(0.008)
In Range	0.021***	0.016***	0.014***	0.007***	0.011***	0.021***	0.014**	0.038***	0.019**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)	(0.005)	(0.008)
1-6 After	-0.004	0.002	0.002	-0.001	0.005	-0.004	-0.003	0.004	-0.011*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)	(0.006)
7+ After	0.004	0.001	0.004	0.001	-0.001	0.003	-0.002	-0.000	0.006
	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)	(0.007)
N	519,028	519,028	519,028	519,028	456,944	519028	519,028	519,028	519,028

Notes: Effect sizes are in standard deviations. Heteroskedasticity robust standard errors clustered by counselor and student are in parentheses. (*p<.10 **p<.05 *** p<.01). All estimates are based on regressions of residualized student outcomes on counselor value-added (in SDs), conditional on school by year fixed effects. Counselor value-added measures are interacted with indicators for a student's distance (in terms of letters) from assignment to that counselor. In most cases, distance is binned by groups of six letters. In the specification with the donut, the first bin excludes students within one letter of the assignment threshold. The coefficients indicate the relationship between a counselor's value-added and student outcomes for students of the relevant distance from the assignment threshold. Students in-range have last names that indicate they are actually assigned to that counselor while all other students are outside the assignment range - by the noted number of letters. Student observations are repeated since there are multiple counselors in each school (and year) so students will typically be in the assignment range for one counselor and then outside it for 1-5 counselors. Student outcomes are residualized on the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor) and a vector of student baseline controls. 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. College attendance is based on attendance within six months of completing high school.

Table 7: Impact of Predicted Counselor Effectiveness by Student Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Prior Achievement						
Low Achievers	0.032***	0.025***	0.023***	0.016***	0.023***	0.067***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
High Achievers	0.008***	0.016***	0.015***	0.012***	0.011***	0.032***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
P-value Difference	0.00	0.03	0.08	0.00	0.16	0.00
Low Achiever Mean	0.79	0.50	0.32	0.37	0.21	-0.13
High Achiever Mean	0.95	0.82	0.74	0.74	0.54	0.62
(B) By Income						
Low Income	0.031***	0.024***	0.018***	0.014***	0.021***	0.061***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.009)
High Income	0.014***	0.018***	0.019***	0.013***	0.015***	0.043***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)
P-value Difference	0.00	0.20	0.76	0.83	0.18	0.06
Low Income Mean	0.76	0.46	0.28	0.18	0.34	-0.22
High Income Mean	0.92	0.76	0.65	0.47	0.67	0.47
(C) By Race						
Non-White	0.024***	0.016***	0.012***	0.010***	0.015***	0.044***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.009)
White	0.019***	0.021***	0.021***	0.015***	0.017***	0.051***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)
P-value Difference	0.21	0.27	0.08	0.58	0.11	0.48
Non-white Mean	0.78	0.54	0.38	0.43	0.26	-0.06
White Mean	0.89	0.69	0.58	0.60	0.41	0.33

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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 test students and those below average are referred to as low test students. Panel (B) shows estimates separately by whether the student received free or reduced-price lunch in 8th grade. Low Inc refers to students who received free or reduced-price lunch while High Inc 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. These results are based on the leave-year-out estimates of effectiveness.

Table 8: Predicted Counselor Effectiveness (in SDs) and Educational Attainment

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Highly Selective Coll (4)	Persist 1st Year (5)	Bachelor's Degree (6)	Education Index (7)
(A) Overall Effects							
Composite Index	0.020***	0.020***	0.019***	0.006***	0.017***	0.012***	0.049***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)
(B)Intermediate Indices							
Cognitive Skills	0.001	0.007**	0.005*	0.003	0.004	-0.001	0.011*
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
Non-Cognitive Skills	0.002	-0.001	-0.003**	-0.000	-0.003**	-0.000	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
College Readiness	0.013***	0.009***	0.009***	0.001	0.008***	0.006**	0.026***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)
College Selectivity	0.004	0.012***	0.015***	0.006**	0.014***	0.008**	0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
(C) Long-Term Effects							
Education Index	0.024***	0.025***	0.020***	0.006***	0.022***	0.016***	0.058***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.005)
N	224,563	224,563	224,563	224,563	201,834	128,542	224,563

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, school, grade and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced price lunch, receipt of title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, days truant, indicators for race (Black, white, Asian or Hispanic) and gender. Counselor effectiveness is in standard deviation units and is based on the leave-year-out empirical Bayes estimates of effectiveness. The estimates indicate how much a predicted one standard deviation better counselor increases educational attainment. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Bachelor's degree completion is measured for all high school cohorts from 2015 or earlier.

Table 9: Impact of First Counselor's Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Race Match						
Race Match	0.019***	0.016**	0.011*	0.004	0.022***	0.030**
	(0.006)	(0.006)	(0.007)	(0.005)	(0.007)	(0.014)
Non-White Match	0.028**	0.018*	0.015	0.004	0.033***	0.037
	(0.012)	(0.011)	(0.011)	(0.009)	(0.012)	(0.023)
White Match	0.017***	0.018**	0.011	0.004	0.020**	0.034*
	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)	(0.019)
N	218,673	218,673	218,673	218,673	196,408	218,673
(B) Undergrad College						
In Massachusetts	0.012**	0.011*	0.006	0.007*	0.006	0.026**
	(0.005)	(0.006)	(0.006)	(0.003)	(0.007)	(0.011)
Selective	0.010	0.008	-0.001	-0.001	0.010	0.007
	(0.009)	(0.009)	(0.008)	(0.005)	(0.008)	(0.020)
N	46,013	46,013	46,013	46,013	40,196	46,013
(C) Years Experience (9th Grade)						
Novice	-0.007	-0.005	0.006	0.004	0.000	-0.003
	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.009)
Log(Years)	-0.008***	-0.005	0.003	0.001	0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
N	139,459	139,459	139,459	139,459	121,099	139,459

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 student 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) ais 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 10: Impact of Caseloads on Student Outcomes

	Grade 9 Caseload	Grade 11 Caseload				
	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) OLS Caseload						
Caseload (in 100s)	-0.028**	-0.018	-0.031*	-0.039**	-0.018	-0.095**
	(0.012)	(0.011)	(0.015)	(0.012)	(0.012)	(0.032)
(B) Student Controls						
Caseload (in 100s)	-0.011	-0.002	-0.009	-0.020***	0.003	-0.041**
	(0.007)	(0.005)	(0.007)	(0.006)	(0.005)	(0.014)
(C) School, Year FE						
Caseload (in 100s)	-0.003	-0.000	-0.000	-0.000	0.000	-0.012*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.007)
(D) Within School Variation Counselors						
Caseload (in 100s)	0.001	-0.002	-0.002	-0.002	-0.003	-0.007
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
(E) Within School Variation HS Size						
Caseload (in 100s)	-0.013**	-0.007	-0.008*	-0.006**	-0.004	-0.014
	(0.004)	(0.004)	(0.004)	(0.002)	(0.005)	(0.009)
(F) Within School Variation Other Grade Size						
Caseload (in 100s)	-0.016***	-0.008	-0.008	-0.006*	-0.005	-0.016
	(0.005)	(0.005)	(0.005)	(0.003)	(0.006)	(0.012)
For High Achievers	-0.016**	-0.003	-0.001	-0.009	-0.001	-0.023
	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.021)
For Low Achievers	-0.017**	-0.018**	-0.026**	-0.009	-0.010	-0.026
	(0.007)	(0.007)	(0.009)	(0.006)	(0.008)	(0.019)
For High Income	-0.016**	-0.011	-0.013	-0.013**	-0.010	-0.033
	(0.007)	(0.008)	(0.008)	(0.006)	(0.008)	(0.023)
For Low Income	-0.018**	0.000	0.002	0.008	0.006	0.021
	(0.008)	(0.010)	(0.009)	(0.007)	(0.009)	(0.022)
N	661,926	726,109	726,109	726,109	660,397	726,109

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, and whether they are low income (receive free or reduce-price lunch) or not. 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. College 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

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	In Sample	Not in Sample
(A) Demographics and Achievement			
White	0.65	0.80	0.56
African American	0.11	0.05	0.15
Hispanic	0.17	0.08	0.22
Asian	0.04	0.04	0.04
English Language Learner	0.05	0.02	0.07
Students with Disabilities	0.20	0.15	0.23
Low-Income	0.39	0.25	0.48
Accountability Percentile	0.50	0.57	0.45
(B) Location and Size			
Urban	0.22	0.12	0.28
Suburban	0.56	0.66	0.50
Rural	0.20	0.22	0.19
Traditional School	0.78	0.92	0.70
Charter School	0.10	0.03	0.14
Vocational School	0.10	0.05	0.13
Per-Pupil Spending	14,629	13,688	15,268
(C) Postsecondary Plans			
Plan to Attend Four-Year College	54%	65%	46%
Plan to Attend Two-Year College	25%	20%	29%
Plan to Work	8%	7%	9%
Plan to Join Military	2%	2%	3%
N	390	146	244

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.

Table A.3: Validity of Predicted Effects without Imputed Assignments

	Including Imputations		Not Always Imputed		Never Imputed	
	Predicted Outcome (1)	Actual Outcome (2)	Predicted Outcome (3)	Actual Outcome (4)	Predicted Outcome (5)	Actual Outcome (6)
VA Measure						
High School Graduation	0.008	1.112***	0.000	0.849***	0.022***	1.016***
	(0.005)	(0.111)	(0.002)	(0.046)	(0.006)	(0.145)
Attend College	0.021	0.908***	0.000	0.615***	0.056***	0.793***
	(0.013)	(0.086)	(0.005)	(0.044)	(0.014)	(0.112)
Four-year College	-0.006	-0.006	-0.003	0.865***	0.014	1.114***
	(0.022)	(0.022)	(0.011)	(0.087)	(0.028)	(0.193)
Composite Index	-0.018	1.155***	-0.017	0.918***	0.064***	0.999***
	(0.021)	(0.086)	(0.013)	(0.057)	(0.024)	(0.122)
Non-Cognitive Skills	-0.002	0.885*** -0.002	0.841***	0.002	1.049***	
	(0.001)	(0.038)	(0.001)	(0.033)	(0.002)	(0.058)
Cognitive Skills	0.038	1.255***	-0.013	1.045***	0.046	0.271**
	(0.053)	(0.154)	(0.045)	(0.149)	(0.029)	(0.124)
College Readiness	-0.032***	1.037***	-0.023***	0.922***	0.037*	1.179***
	(0.011)	(0.091)	(0.008)	(0.071)	(0.020)	(0.146)
College Selectivity	0.023	1.136***	-0.005	0.837***	0.060**	0.937***
	(0.029)	(0.161)	(0.018)	(0.103)	(0.028)	(0.190)
Education Attainment Index	0.007	1.114***	-0.000	0.893***	0.038**	1.073***
	(0.014)	(0.098)	(0.006)	(0.057)	(0.018)	(0.144)

Notes: Heteroskedasticity robust standard errors clustered by counselor and cohort are in parentheses. (*p<.10 **p<.05 *** p<.01). Each estimate comes from a regression of a student's predicted or actual (residual) outcome on their counselor's leave-one-out value-added estimate for the relevant outcome. In all cases, I use the residual outcome, controlling for the first letter of a student's last name, school, grade, and year (when a student was first assigned to the counselor), 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 columns 1, 3, and 5 the outcome is the student's predicted outcome (e.g. high school graduation) based on their seventh grade test scores. In columns 2, 4 and 6, the dependent variable is the student's actual outcome (e.g. high school graduation). Estimates in column 1 and 2 are those from the main sample. Columns 3 and 4 exclude students whose assignments are always imputed. Columns 5 and 6 exclude students whose assignments are imputed at least once (during their high school time). 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.

Table A.4: Impacts of Counselors without Imputed Assignments

	Student Outcomes					Indices			
	Graduate		Attend	College's					
	High School (1)	Attend College (2)	Four-Year College (3)	Graduation Rate (4)	Persist 1st Year (5)	Cognitive Skills (6)	Non-Cognitive Skills (7)	College Readiness (8)	College Selectivity (9)
(A) Never Imputed									
Composite Index	0.014***	0.016***	0.017***	0.011***	0.011***	0.027***	0.037***	0.055***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.008)	(0.005)
Education Index	0.024***	0.023***	0.021***	0.014***	0.017***	0.023***	-0.004	0.060***	0.040***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.006)	(0.008)	(0.009)	(0.007)
(B) Not Always Imputed									
Composite Index	0.038***	0.033***	0.028***	0.016***	0.029***	0.017***	0.069***	0.084***	0.047***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.005)	(0.008)	(0.006)	(0.004)
Education Index	0.043***	0.036***	0.030***	0.015***	0.032***	0.019***	0.030***	0.078***	0.047***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.005)	(0.007)	(0.005)	(0.004)
(C) Including Imputations									
Composite Index	0.021***	0.022***	0.020***	0.014***	0.018***	0.020***	0.070***	0.076***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.009)	(0.007)	(0.005)
Education Index	0.026***	0.027***	0.022***	0.015***	0.024***	0.024***	0.012	0.062***	0.041***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.009)	(0.006)	(0.005)

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

Table A.5: Impacts of Counselors with Reweighting to Represent State Population

	Student Outcomes					Indices			
	Graduate		Attend	College's					
	High School (1)	Attend College (2)	Four-Year College (3)	Graduation Rate (4)	Persist 1st Year (5)	Cognitive Skills (6)	Non-Cognitive Skills (7)	College Readiness (8)	College Selectivity (9)
(A) Propensity Scores based on Student Characteristics									
Composite Index	0.025***	0.024***	0.022***	0.017***	0.021***	0.010	0.114***	0.100***	0.043***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.010)	(0.015)	(0.009)	(0.008)
Education Index	0.033***	0.033***	0.024***	0.016***	0.030***	0.020**	0.032**	0.077***	0.046***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)	(0.016)	(0.009)	(0.008)
(B) Propensity Scores based on School Characteristics									
Composite Index	0.074***	0.063***	0.046***	0.027***	0.045***	0.008	0.250***	0.093***	0.062***
	(0.015)	(0.012)	(0.010)	(0.006)	(0.011)	(0.023)	(0.049)	(0.027)	(0.017)
Education Index	0.075***	0.050***	0.041***	0.024**	0.031**	0.011	0.126**	0.107***	0.038
	(0.015)	(0.016)	(0.014)	(0.009)	(0.015)	(0.022)	(0.056)	(0.027)	(0.036)
(C) Propensity Scores based on Student and School Characteristics									
Composite Index	0.026*	0.047***	0.033***	0.018**	0.028**	-0.009	0.149***	0.094***	0.042
	(0.016)	(0.014)	(0.011)	(0.008)	(0.012)	(0.023)	(0.035)	(0.028)	(0.026)
Education Index	0.042**	0.052***	0.037***	0.019**	0.035**	0.008	0.077**	0.101***	0.048*
	(0.019)	(0.016)	(0.012)	(0.008)	(0.014)	(0.022)	(0.038)	(0.028)	(0.027)

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

Table A.6: Correlation in Student Outcomes

	Graduate High School (1)	Attend College (2)	Attend Four-year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Earn BA Degree (6)	HS GPA (7)	HS Classes Failed (8)	10th gr. Math Test (9)	10th gr. Reading Test (10)	Log Absences (11)	Log Days Truant (12)	Log. Suspensions (13)	HS Dropout Score (14)	Max SAT Tests (15)	Any AP (16)
Graduate HS	1.000															
Attend College	0.500	1.000														
Attend Four-Year	0.405	0.765	1.000													
College Grad Rate	0.357	0.634	0.876	1.000												
Persist 1st Year	0.424	0.815	0.740	0.638	1.000											
Bachelor's Degree	0.332	0.607	0.735	0.691	0.687	1.000										
HS GPA	0.433	0.507	0.568	0.621	0.522	0.543	1.000									
Classes Failed	-0.414	-0.369	-0.360	-0.360	-0.353	-0.309	-0.670	1.000								
10th gr Math	0.283	0.409	0.512	0.593	0.423	0.468	0.642	-0.366	1.000							
10th gr Reading	0.292	0.414	0.494	0.562	0.419	0.452	0.606	-0.364	0.734	1.000						
Log Absences	-0.152	-0.253	-0.293	-0.335	-0.289	-0.315	-0.497	0.406	-0.355	-0.279	1.000					
Log Days Truant	-0.079	-0.121	-0.139	-0.174	-0.126	-0.135	-0.260	0.257	-0.191	-0.171	0.330	1.000				
Log Suspensions	-0.226	-0.246	-0.263	-0.269	-0.264	-0.305	-0.349	0.240	-0.259	-0.252	0.285	-0.062	1.000			
HS Dropout	-0.417	-0.232	-0.188	-0.187	-0.200	-0.160	-0.324	0.315	-0.164	-0.172	0.244	0.083	0.220	1.000		
Max SAT	0.086	0.181	0.358	0.538	0.223	0.348	0.570	-0.166	0.778	0.665	-0.202	-0.078	-0.181	-0.034	1.000	
Any AP Test	0.295	0.404	0.499	0.563	0.424	0.476	0.523	-0.256	0.558	0.513	-0.246	-0.067	-0.217	-0.141	0.550	1.000
College Mean Inc	0.337	0.595	0.686	0.839	0.562	0.567	0.561	-0.313	0.549	0.507	-0.310	-0.168	-0.225	-0.178	0.521	0.522

Notes: These estimates indicate the correlation of student outcomes for all students in my sample. College attendance is based on attendance within 6 months of finishing high school. Persistence and college graduation rates are zero for students who do not attend college. College's graduation rate refers to the average historical 6 year graduation rate at the college a student attends. Test scores are based on the 10th grade Massachusetts state test (MCAS). HS GPA refers to students cumulative GPA at the end of high school. HS classes failed counts the number of classes a student failed in high school. Log absences takes the log of days absent plus one. Log of days truant and log of days suspended are similarly defined. HS dropout is an indicator for having officially dropped out of high school. Max SAT score refers to the student's maximum SAT score among all times they took it. Any AP tests is an indicator for taking any AP tests.

Table A.7: Predictors of the Number of Students Matched to a Counselor

(A) Student Predictors								
	8th Grade		Low					
	Test Scores	Absences	Income	Male	White	Asian	Hispanic	Black
Caseload (in 10s)	0.0002	0.0004	-0.0000	0.0002	0.0005*	-0.0004	-0.0003	0.0002*
	(0.0004)	(0.0005)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)

(B) Counselor Predictors							
	Log					Institution type for Undergrad	
	Experience	Novice	Male	White	NonWhite	Massachusetts	Selective
Caseload (in 10s)	-0.001	-0.000	0.005	-0.001	0.001	0.001	0.004
	(0.004)	(0.002)	(0.003)	(0.001)	(0.001)	(0.006)	(0.003)
N	218,641	218,641	218,604	218,604	218,604	45,997	45,997

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include school by year fixed effects. These estimates are from regressions of student or counselor characteristics on the number of students matched to the counselor. The independent variable is divided by ten so the coefficient indicates how a ten student increase in the number of students matched to the counselor is associated with different student or counselor characteristics. Each coefficient comes from a separate regression. Counselor years of experience are based on when the student is in 9th grade.

Table A.8: Regression Discontinuity Estimates of Counselor Effects in Units of Outcome Measure

	Donut - (Excluding Students on the Margin)				Without Donut			
	Graduate High School	Attend College	Education Index	Composite Index	Graduate High School	Attend College	Education Index	Composite Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Letters from Assignment Range								
7+ Before	0.164*	0.017	0.051	0.061	0.158	0.016	0.052	0.067
	(0.099)	(0.079)	(0.089)	(0.071)	(0.096)	(0.078)	(0.089)	(0.070)
1-6 Before	0.007	0.061	0.082	0.134*	0.000	0.060	0.084	0.141*
	(0.116)	(0.091)	(0.103)	(0.080)	(0.114)	(0.089)	(0.103)	(0.080)
In Range	0.827***	0.638***	0.698***	0.477***	0.822***	0.637***	0.700***	0.483***
	(0.137)	(0.095)	(0.113)	(0.090)	(0.135)	(0.094)	(0.113)	(0.089)
1-6 After	-0.108	0.097	-0.001	-0.113	-0.149	0.072	0.021	-0.050
	(0.124)	(0.133)	(0.116)	(0.076)	(0.095)	(0.098)	(0.100)	(0.069)
7+ After	0.153	0.024	0.129	-0.004	0.147	0.023	0.131	0.003
	(0.125)	(0.090)	(0.100)	(0.074)	(0.123)	(0.089)	(0.099)	(0.073)

Notes: Effect sizes are in standard deviations. Heteroskedasticity robust standard errors clustered by counselor and student are in parentheses. (*p<.10 **p<.05 *** p<.01). All estimates are based on regressions of residualized student outcomes on counselor value-added (measured in the same units as the outcome), conditional on school by year fixed effects. Effect sizes are in percentage points for columns (1) through (3) and standard deviations of the outcome measure for columns (4) through (8). (These are akin to the validity estimates in Table 3. Counselor value-added measures are interacted with indicators for a student's distance (in terms of letters) from assignment to that counselor. In most cases, distance is binned by groups of six letters. In the specification with the donut, the first bin excludes students within one letter of the assignment threshold. The coefficients indicate the relationship between a counselor's value-added and student outcomes for students of the relevant distance from the assignment threshold. Students in-range have last names that indicate they are actually assigned to that counselor while all other students are outside the assignment range - by the noted number of letters. Student observations are repeated since there are multiple counselors in each school (and year) so students will typically be in the assignment range for one counselor and then outside it for 1-5 counselors. Student outcomes are residualized on the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor) and a vector of student baseline controls. 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. College attendance is based on attendance within six months of completing high school.

Table A.9: Validity of Predicted Effects with Alternate Models

	Simple FE		Letter		Cohort x Letter		Race x Letter	
	Predicted Outcome	Actual Outcome	Predicted Outcome	Actual Outcome	Predicted Outcome	Actual Outcome	Predicted Outcome	Actual Outcome
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VA Measure								
High School Graduation	0.083***	0.965***	0.008	1.068***	0.006	1.035***	0.008	1.066***
	(0.010)	(0.072)	(0.005)	(0.109)	(0.005)	(0.105)	(0.005)	(0.103)
Attend College	0.155***	0.938***	0.019	0.856***	0.014	0.869***	0.019	0.877***
	(0.022)	(0.065)	(0.013)	(0.084)	(0.012)	(0.078)	(0.012)	(0.078)
Four-year College	0.234***	0.979***	-0.010	0.924***	-0.023	0.827***	-0.015	0.898***
	(0.031)	(0.079)	(0.022)	(0.158)	(0.019)	(0.143)	(0.021)	(0.158)
Composite Index	0.280***	0.986***	-0.020	1.097***	-0.032*	1.017***	-0.023	1.078***
	(0.039)	(0.061)	(0.021)	(0.085)	(0.019)	(0.078)	(0.020)	(0.084)
Non-Cognitive Skills	-0.015	0.913***	-0.002	0.882***	-0.003*	0.884***	-0.003*	0.894***
	(0.011)	(0.047)	(0.001)	(0.037)	(0.002)	(0.038)	(0.002)	(0.040)
Cognitive Skills	0.530***	0.991***	0.035	1.244***	0.025	1.146***	0.045	1.235***
	(0.064)	(0.079)	(0.053)	(0.154)	(0.049)	(0.141)	(0.053)	(0.152)
College Readiness	0.117***	0.962***	-0.033***	0.988***	-0.036***	0.974***	-0.035***	0.985***
	(0.031)	(0.060)	(0.011)	(0.087)	(0.011)	(0.081)	(0.011)	(0.083)
College Selectivity	0.317***	1.015***	0.020	1.089***	-0.003	0.969***	0.015	1.054***
	(0.039)	(0.085)	(0.029)	(0.160)	(0.026)	(0.149)	(0.028)	(0.160)
Education Attainment Index	0.166***	0.963***	0.004	1.036***	-0.003	0.983***	0.003	1.031***
	(0.020)	(0.055)	(0.014)	(0.097)	(0.012)	(0.088)	(0.013)	(0.092)

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. College attendance is based on attendance within six months of completing high school.

Table A.10: Counselor Impacts on AP Courses and Tests Taken

	AP Courses				AP Tests		
	Total Courses (1)	AP Calculus (2)	Any AP STEM (3)	Number AP STEM (4)	Any AP Tests (5)	Number AP Tests. (6)	Calculus Test (7)
(A) Outcome-Specific Measure							
Value-Added	0.209***	0.020***	0.039***	0.127***	0.041***	0.363***	0.010***
	(0.014)	(0.003)	(0.003)	(0.010)	(0.002)	(0.031)	(0.001)
(B) Composite Index							
Composite Index	0.075***	0.004**	0.018***	0.030***	0.030***	0.255***	0.002**
	(0.017)	(0.002)	(0.003)	(0.009)	(0.003)	(0.028)	(0.001)
N	187,416	187,879	187,879	187,879	217,310	217,310	217,310

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Panel (A) is based on counselors' estimated value-added on the relevant outcome (e.g., total AP courses in column 1). Panel (B) is based on counselors' estimated value-added on the composite index outcome. The coefficients represent the impact of a one standard deviation improvement in counselor effectiveness (on the measure noted). Columns one through four are based on AP courses indicated in the course records files. These are available from 2011 to 2019. Columns five through seven are based on AP courses taken as recorded in the College Board data files. These are available from 2009 to 2019, so they cover a larger sample than the course records.

Table A.11: Counselor Impacts on Behavior and Achievement in High School

					10th Grade State Test	
	Days Absent (1)	Days Suspended (2)	High School Dropout (3)	High School GPA (4)	Math Test (5)	English Test (6)
(A) Composite Index						
Composite Index	-0.012**	-0.054***	-0.005***	0.016***	0.018***	0.021***
	(0.005)	(0.008)	(0.001)	(0.006)	(0.004)	(0.004)
(B) Outcome-Specific Measure						
Value-Added	0.072***	0.015	0.007***	0.058***	0.047***	0.056***
	(0.009)	(0.010)	(0.002)	(0.004)	(0.005)	(0.005)
N	224,563	224,563	224,563	187,821	203,558	204,167

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Panel (A) is based on counselors' estimated value-added on the relevant outcome (e.g., log of days absent in column 1). Panel (B) is based on counselors' estimated value-added on the composite index outcome. The coefficients represent the impact of a one standard deviation improvement in counselor effectiveness (on the measure noted). For days absent and days suspended, I take the log of days plus one to deal with large values and zeros.

Table A.12: Counselor Impacts on SAT Taking and College Type

	SAT			College Selectivity			College Match	
	Took SAT (1)	Max SAT all Students (2)	Max SAT Among SAT Takers (3)	Selective College (4)	Highly Selective College (5)	College Mean Inc (6)	Under-match (7)	Over-match (8)
(A) Composite Index								
Composite Index	0.035***	3.877***	13.507***	0.018***	0.006***	933.468***	0.004*	0.003
	(0.004)	(0.918)	(1.495)	(0.002)	(0.001)	(108.947)	(0.002)	(0.002)
(B) Outcome-Specific Measure								
Value-Added	0.040***	4.478***	17.121***	0.021***	0.005	1165.395***	0.011***	
	(0.005)	(1.104)	(1.959)	(0.004)	(0.005)	(171.458)	(0.003)	
N	224,563	143,286	224,563	224,563	224,563	224,563	119,714	

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Panel (A) is based on counselors' estimated value-added on the relevant outcome (e.g., SAT taking in column 1). Panel (B) is based on counselors' estimated value-added on the composite index outcome. The coefficients represent the impact of a one standard deviation improvement in counselor effectiveness (on the measure noted). Undermatch is defined as attending a college where the student's SAT score is above the 75th percentile of SAT scores among accepted students. Overmatch is defined as attending a college where the student's SAT score is below the 25th percentile of SAT scores among accepted students.

Table A.13: Counselor Impacts on College Majors

	STEM Major (1)	Science (2)	Engineering, CS or IT (3)	Social Sciences (4)	Health (5)	Business (6)
(A) Composite Index						
Composite Index	0.010***	-0.000	0.002*	-0.002	-0.005***	-0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
(B) Education Index						
Education Index	0.011***	0.000	0.003**	-0.003*	-0.005**	-0.005**
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
N	118,719	148,519	148,519	148,519	148,519	148,519

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Panel (A) is based on counselors' estimated value-added on the relevant outcome (e.g., STEM majors in column 1). Panel (B) is based on counselors' estimated value-added on the composite index outcome. The coefficients represent the impact of a one standard deviation improvement in counselor effectiveness (on the measure noted). Majors are based on CIP codes reported for students who attend college. The major analyses are restricted to students who attend college and the match ones are restricted to students attending a four-year college.

Table A.14: Impact of a Predicted 1 SD Better Counselor by Additional Subgroups

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Gender						
Male	0.022***	0.019***	0.019***	0.013***	0.017***	0.050***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
Female	0.018***	0.021***	0.019***	0.014***	0.016***	0.049***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.20	0.63	1.00	0.76	0.82	0.90
Male Mean	0.85	0.60	0.47	0.34	0.50	0.13
Female Mean	0.89	0.72	0.59	0.41	0.63	0.36
(B) By Prior Achievement						
Low Test	0.034***	0.026***	0.023***	0.015***	0.023***	0.069***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.008)
Med Test	0.012***	0.022***	0.021***	0.015***	0.020***	0.046***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.007)
High Test	0.006***	0.012***	0.012***	0.011***	0.007*	0.025***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.007)
Low Test Score Mean	0.78	0.49	0.31	0.20	0.36	-0.16
Middle Test Score Mean	0.92	0.74	0.60	0.39	0.63	0.42
High Test Score Mean	0.96	0.86	0.80	0.61	0.79	0.71
(C) By Location						
Rural	0.012***	0.014**	0.015***	0.011***	0.008	0.034***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.012)
Suburban	0.020***	0.023***	0.021***	0.016***	0.018***	0.054***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.006)
Urban	0.027***	0.019***	0.017***	0.012***	0.021***	0.053***
	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)	(0.012)
N	219,679	219,679	219,679	219,679	197,383	219,679
Rural Mean	0.88	0.67	0.55	0.58	0.39	0.28
Suburban Mean	0.89	0.69	0.58	0.60	0.41	0.34
Urban Mean	0.77	0.52	0.33	0.40	0.22	-0.12

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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.

Table A.15: Impact of a Predicted 1 SD Better Counselor by School Subgroups

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year College (5)	Education Index (6)
(A) School Percent Free/Reduced Lunch						
Low Percent FRPL	0.024***	0.021***	0.018***	0.014***	0.019***	0.053***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
High Percent FRPL	0.015***	0.019***	0.020***	0.014***	0.014***	0.045***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.02	0.73	0.71	0.96	0.26	0.44
High Percent FRPL Mean	0.82	0.57	0.40	0.26	0.46	0.02
Low Percent FRPL Mean	0.91	0.76	0.67	0.49	0.67	0.48
(B) School Persistent Poverty						
Low Poverty	0.024***	0.020***	0.017***	0.012***	0.019***	0.051***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.009)
High Poverty	0.017***	0.020***	0.020***	0.015***	0.015***	0.048***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)
P-value Difference	0.14	0.97	0.61	0.47	0.37	0.72
High Poverty Mean	0.80	0.52	0.35	0.23	0.41	-0.08
Low Poverty Mean	0.90	0.74	0.64	0.46	0.65	0.43
(C) School Percent High Needs						
Lower Needs	0.024***	0.021***	0.018***	0.014***	0.019***	0.053***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
Higher Needs	0.015***	0.019***	0.019***	0.013***	0.014***	0.045***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.03	0.61	0.84	0.86	0.23	0.37
Higher Needs Mean	0.82	0.56	0.39	0.26	0.45	0.01
Lower Needs Mean	0.91	0.76	0.67	0.49	0.68	0.48
(D) School Accountability Level						
Level 2-3 (Worse)	0.019***	0.019***	0.018***	0.014***	0.014***	0.047***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
Level 1 (Better)	0.021***	0.022***	0.019***	0.013***	0.020***	0.052***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.53	0.51	0.94	0.74	0.15	0.61
Level 1 Mean	0.91	0.72	0.61	0.44	0.63	0.39
Level 2-3 Mean	0.83	0.61	0.46	0.32	0.51	0.12

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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 (B) uses the average years that students in a particular school and cohort receive free or reduced-price lunch to construct a measure of persistent poverty (Michelmore & Dynarski, 2017). Schools are split by whether they are above or below the average for years the mean student receives frpl (conditional on the cohort to account for the years of data available). Panel (D) is based on the school accountability level reported by the state. Level one is the best and level three is the worst.

Table A.16: Impact of a Predicted 1 SD Better Counselor by Caseload Size

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Gender						
Large Caseload	0.010***	0.012***	0.019***	0.014***	0.014***	0.034***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.009)
Small Caseload	0.020***	0.020***	0.019***	0.014***	0.017***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
P-value Difference	0.00	0.01	0.91	0.93	0.28	0.02
Large Caseload Mean	0.86	0.65	0.51	0.35	0.55	0.21
Small Caseload Mean	0.87	0.68	0.55	0.39	0.58	0.28

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Small caseloads are defined as fewer than 250 students and large caseloads are defined as 250 or more per year. This is close to the state average and is the caseload recommended by the American School Counselors Association. Caseloads are determined by the number of students I observe in each counselors assignment window for last names.

Table A.17: Group Specific Impacts of Counselors

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Prior Achievement						
High Achievers	0.020***	0.034***	0.038***	0.021***	0.027***	0.077***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Low Achievers	0.019***	0.032***	0.048***	0.036***	0.030***	0.082***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.00	0.00	0.00	0.00	0.00	0.00
High Achiever Mean	0.94	0.81	0.73	0.73	0.53	0.60
Low Achiever Mean	0.80	0.47	0.27	0.35	0.16	-0.18
(B) By Income						
High Income	0.017***	0.025***	0.025***	0.016***	0.025***	0.055***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
Low-Income	0.028***	0.040***	0.040***	0.032***	0.042***	0.091***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)
P-value Difference	0.00	0.00	0.00	0.00	0.00	0.00
High Income Mean	0.92	0.76	0.65	0.67	0.47	0.47
Low-Income Mean	0.76	0.46	0.28	0.34	0.18	-0.22
(C) By Race						
White	0.020***	0.024***	0.022***	0.016***	0.020***	0.055***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)
Non-White	0.023***	0.026***	0.022***	0.019***	0.029***	0.059***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)	(0.011)
P-value Difference	0.00	0.00	0.00	0.00	0.00	0.00
White	0.89	0.69	0.58	0.60	0.41	0.33
Non-White	0.78	0.54	0.38	0.43	0.26	-0.06

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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 test students and those below average are referred to as low test students. Panel (B) shows estimates separately by whether the student received free or reduced-price lunch in 8th grade. Low Inc refers to students who received free or reduced-price lunch while High Inc 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 for the noted subgroup. These results are based on the leave-year-out estimates of effectiveness calculated separately by the noted group (e.g. for white vs nonwhite students).

Table A.18: Correlation of Group-Specific Value-Added Across Groups

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)	Education Index (7)	Non-Cognitive Skills (8)	Cognitive Skills (9)	College Readiness (10)	College Selectivity (11)
VA by Achievement	-0.064***	-0.221***	-0.296***	-0.209***	-0.252***	-0.007***	-0.176***	-0.015***	0.301***	0.006**	-0.225***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VA by Income	0.170***	-0.111***	-0.158***	-0.151***	-0.188***	0.117***	0.011***	0.067***	0.241***	0.133***	-0.143***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)
VA by Race	0.328***	0.106***	0.037***	-0.063***	0.045***	0.212***	0.204***	0.135***	0.161***	0.330***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). These estimates show the correlation between counselor value-added for one group relative to the counselor's value added for the second group. First, this is done by achievement, where students with scores above the state average are classified as high achieving students and those below average are referred to as low achieving students. Second, this is done by whether the student received free or reduced-price lunch in 8th grade. Low Inc refers to students who received free or reduced-price lunch while High Inc refers to those who did not. (These are the best measures of income available in the data.) Third, value-added is estimated separately for white and non-white students. These results are based on the leave-year-out estimates of effectiveness calculated separately by the noted groups. The N for VA by achievement is 217,675. For VA by Income it is 221,733, and for VA by race it is 219,619.

Table A.19: Impact of Counselor Value-Added for Course-Taking on Long-Term Outcomes

	Attend College (1)	Attend Four-Year (2)	STEM Major (3)	College Graduation Rate (4)	Persist 1st Year (5)
(A) VA for Any APs					
Any AP Tests	0.013***	0.014***	0.003*	0.009***	0.012***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
(B) VA Total APs					
Number of AP Tests	0.013***	0.015***	0.004**	0.011***	0.012***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
(C) VA AP Calculus					
AP Calculus	0.002	0.003**	-0.000	0.001	0.003*
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
N	224,563	224,563	118,719	224,563	201,834

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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. Panel (A) is based on counselors' estimated value-added for taking any AP tests. Panel (B) is based on counselors' estimated value-added on the number of AP tests taken. Panel (C) is based on counselors' estimated value-added on taking the AP Calculus test. I use AP test taking data rather than course enrollments because course data are not available for all cohorts. The coefficients represent the impact of a one standard deviation improvement in counselor effectiveness (on the measure noted). Majors are based on CIP codes reported for students who attend college. STEM major is only defined for students who attend college.

Table A.20: Correlation in Counselor Value-Added Measures

	Indices								
	Composite Index (1)	Non-Cognitive Skills (2)	Cognitive Skills (3)	College Readiness (4)	College Selectivity (5)	Education Index (6)	Graduate High School (7)	Attend College (8)	Highly Selective (9)
(A) Indices									
Composite Index	1.000								
Non-Cognitive Skills	0.425	1.000							
Cognitive Skills	0.541	-0.063	1.000						
College Ready	0.779	0.236	0.228	1.000					
College Quality	0.743	0.042	0.452	0.461	1.000				
Education Index	0.832	0.150	0.392	0.592	0.677	1.000			
(A) Outcome-based VA									
Graduate High School	0.611	0.219	0.202	0.467	0.329	0.762	1.000		
Attend College	0.611	0.219	0.202	0.467	0.329	0.762	1.000	1.000	
Highly Selective College	0.332	-0.008	0.221	0.162	0.689	0.201	0.065	0.065	1.000
Persist 1st Year	0.610	0.078	0.312	0.432	0.564	0.742	0.391	0.391	0.205

Notes: Estimates indicate the correlation of counselor value-added measures. These are based on the leave-year out value-added estimates for counselors in the main sample.

Table A.21: Counselor Effects with Logit Specification (Odds Ratios)

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	Persist 1st Year (4)
(A) Composite Index				
Composite Index	1.212***	1.103***	1.103***	1.071***
	(0.023)	(0.014)	(0.015)	(0.013)
(B) Additional Indices				
Behavior Index	1.020*	0.998	0.996	0.992
	(0.012)	(0.007)	(0.007)	(0.007)
HS Index	1.085***	1.077***	1.070***	1.053***
	(0.026)	(0.015)	(0.015)	(0.014)
College Readiness Index	1.151***	1.056***	1.067***	1.040***
	(0.024)	(0.012)	(0.013)	(0.012)
College Quality Index	1.183***	1.110***	1.119***	1.087***
	(0.032)	(0.020)	(0.020)	(0.016)
Edu Index	1.260***	1.137***	1.117***	1.102***
	(0.028)	(0.017)	(0.018)	(0.014)
(C) Education Outcomes				
Outcome-specific VA	1.231***	1.106***	1.099***	1.077***
	(0.029)	(0.013)	(0.022)	(0.019)
N	224,563	224,563	224,563	201,834

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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.

Table A.22: Regression Discontinuity Estimates of Counselor Effects for Additional Outcomes

	Four-Year College (1)	Graduation Rate (2)	Persist 1st Year (3)	Cognitive Skills (4)	Non-Cognitive Skills (5)	College Readiness (6)	College Selectivity (7)
Letters from Assignment Range							
7+ After	0.171	0.072	-0.044	0.063	-0.020	-0.011	0.121
	(0.166)	(0.140)	(0.147)	(0.116)	(0.025)	(0.059)	(0.165)
2-6 After	0.049	-0.126	0.078	-0.128	-0.026	0.000	-0.432***
	(0.167)	(0.144)	(0.168)	(0.092)	(0.030)	(0.060)	(0.166)
In Range	0.629***	0.452***	0.467***	0.465***	0.116**	0.454***	0.418**
	(0.157)	(0.128)	(0.150)	(0.099)	(0.046)	(0.065)	(0.170)
2-6 Before	0.246	0.179	0.001	0.105	0.001	0.161**	0.152
	(0.172)	(0.151)	(0.185)	(0.105)	(0.024)	(0.068)	(0.173)
7+ Before	-0.006	0.047	0.050	0.029	0.053**	0.147***	-0.127
	(0.138)	(0.115)	(0.135)	(0.103)	(0.026)	(0.057)	(0.150)

Notes: Heteroskedasticity robust standard errors clustered by counselor and student are in parentheses. (*p<.10 **p<.05 *** p<.01). All estimates are based on regressions of residualized student outcomes on counselor value-added, conditional on school by year fixed effects. Counselor value-added measures are interacted with indicators for a student's distance (in terms of letters) from assignment to that counselor. In most cases, distance is binned by groups of six letters. In the specification with the donut, the first bin excludes students within one letter of the assignment threshold. The coefficients indicate the relationship between a counselor's value-added and student outcomes for students of the relevant distance from the assignment threshold. Students in-range have last names that indicate they are actually assigned to that counselor while all other students are outside the assignment range - by the noted number of letters. Student observations are repeated since there are multiple counselors in each school (and year) so students will typically be in the assignment range for one counselor and then outside it for 1-5 counselors. Student outcomes are residualized on the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor) and a vector of student baseline controls. 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. College attendance is based on attendance within six months of completing high school.

Table A.23: Impact of Additional Counselor Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Gender Match						
Gender Match	-0.004*	-0.002	-0.005*	-0.000	-0.001	-0.005
	(0.002)	(0.003)	(0.003)	(0.000)	(0.003)	(0.004)
Female Match	-0.003	-0.002	-0.005	-0.000	-0.001	-0.003
	(0.003)	(0.004)	(0.004)	(0.000)	(0.004)	(0.007)
Male Match	-0.006*	-0.002	-0.006*	-0.000	-0.002	-0.008
	(0.003)	(0.004)	(0.004)	(0.000)	(0.004)	(0.006)
N	218,673	218,673	218,673	218,673	196,408	218,673
(B) Experience						
Teacher	-0.009***	-0.006*	-0.002	0.000	-0.003	-0.016**
	(0.003)	(0.003)	(0.004)	(0.000)	(0.003)	(0.007)
Supervisor	0.001	-0.003	-0.006	-0.000	-0.011	-0.015
	(0.005)	(0.006)	(0.007)	(0.000)	(0.007)	(0.011)
N	218,673	218,673	218,673	218,673	196,408	218,673
(C) Education						
Master's in MA	0.000	-0.006	-0.013*	-0.000	-0.006	-0.025**
	(0.006)	(0.006)	(0.007)	(0.000)	(0.005)	(0.010)
N	49,001	49,001	49,001	49,001	42,640	49,001

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 student race and gender. They also include controls for the student's 8th grade test scores, English language proficiency, special education receipt, receipt of free or reduced-price lunch, receipt of Title 1 services, existence of a 504 plan, enrollment in 8th grade in an MA public school, days absent, and days truant. Estimates are based on the first counselor to which a student is quasi-randomly assigned. College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school. Teacher is an indicator for whether the counselor has a teaching license. Supervisor is an indicator for whether the counselor is a counseling supervisor while the student is assigned to that counselor.

Table A.24: 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	0.006	0.011**	-0.002	-0.005	0.009*	0.000*	0.009***	0.006***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.000)	(0.003)	(0.002)
Large Coll	0.007	-0.004	-0.008	0.009	0.000	0.000	0.007**	-0.003
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.000)	(0.003)	(0.002)
Private Coll	-0.009	0.001	0.006	0.000	-0.003	-0.000**	-0.006*	-0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.000)	(0.003)	(0.002)
High Sel. Coll	-0.006	-0.001	-0.004	0.001	-0.000	-0.000	0.001	0.002
	(0.009)	(0.006)	(0.005)	(0.008)	(0.003)	(0.000)	(0.004)	(0.003)
Elite Coll	-0.027***	-0.011	-0.010	-0.008	-0.008	-0.000**	0.003	0.007
	(0.010)	(0.007)	(0.007)	(0.007)	(0.006)	(0.000)	(0.005)	(0.004)
N	46,013	46,013	46,013	46,013	46,013	46,013	46,013	46,013
(B) Among College Attendees								
Coll in MA	0.006	-0.000	-0.019***	-0.006	0.012*	0.000**	0.016***	0.010***
	(0.006)	(0.004)	(0.007)	(0.007)	(0.006)	(0.000)	(0.004)	(0.003)
Large Coll	0.010*	-0.000	-0.006	0.010	-0.001	0.000**	0.008*	-0.006*
	(0.005)	(0.006)	(0.009)	(0.008)	(0.008)	(0.000)	(0.005)	(0.003)
Private Coll	-0.015***	0.001	0.008	0.001	-0.004	-0.000***	-0.009*	-0.004
	(0.005)	(0.004)	(0.006)	(0.007)	(0.006)	(0.000)	(0.004)	(0.003)
High Sel. Coll	-0.004	-0.001	-0.002	0.006	0.001	-0.000	0.001	0.003
	(0.006)	(0.006)	(0.005)	(0.009)	(0.005)	(0.000)	(0.005)	(0.004)
Elite Coll	-0.016**	-0.001	0.001	-0.008	-0.004	-0.000**	0.007	0.010**
	(0.006)	(0.008)	(0.007)	(0.009)	(0.007)	(0.000)	(0.006)	(0.005)
N	30,345	30,345	30,345	30,345	30,345	30,345	30,345	30,345

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 student 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.

Table A.25: Impact of Counselor's College by Student Achievement Levels

	Attend College (1)	Attend Four-Yr (2)	Attend In-State (3)	Attend Public (4)	Attend Large (5)	Small Private (6)	Grad Rate (7)	Highly Selective (8)
(A) High Scoring Students								
College in MA	0.009	0.009	0.009	-0.004	-0.001	0.007	0.000**	0.015***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.007)	(0.000)	(0.006)
Large College	-0.004	0.004	-0.007	-0.004	0.016	-0.007	0.000	0.014**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.010)	(0.009)	(0.000)	(0.006)
Private Coll	0.005	-0.010	0.002	0.007	0.003	0.000	-0.000**	-0.009
	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)	(0.006)	(0.000)	(0.006)
High Sel. College	0.004	-0.006	0.002	0.003	0.009	-0.004	-0.000	-0.003
	(0.006)	(0.007)	(0.008)	(0.009)	(0.012)	(0.007)	(0.000)	(0.006)
ugrad_elite	-0.014	-0.023**	-0.002	-0.017	-0.016	0.006	-0.000**	0.001
	(0.009)	(0.011)	(0.008)	(0.013)	(0.013)	(0.009)	(0.000)	(0.008)
N	21,280	21,280	21,280	21,280	21,280	21,280	21,280	21,280
(B) Low Scoring Students								
College in MA	0.012	0.006	0.015**	0.000	-0.007	0.010*	0.000	0.004
	(0.009)	(0.008)	(0.007)	(0.008)	(0.005)	(0.005)	(0.000)	(0.003)
Large College	-0.003	0.009	-0.001	-0.011	0.002	0.005	0.000	0.001
	(0.009)	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)	(0.000)	(0.002)
Private College	-0.004	-0.009	-0.003	0.003	-0.002	-0.002	-0.000	-0.004
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)	(0.005)	(0.000)	(0.002)
High Sel. College	-0.009	-0.007	-0.004	-0.007	-0.004	0.005	-0.000	0.002
	(0.013)	(0.013)	(0.011)	(0.010)	(0.005)	(0.007)	(0.000)	(0.004)
ugrad_elite	-0.019	-0.031**	-0.023**	0.005	0.000	-0.024***	-0.000*	-0.003
	(0.013)	(0.015)	(0.009)	(0.012)	(0.007)	(0.007)	(0.000)	(0.004)
N	24,732	24,732	24,732	24,732	24,732	24,732	24,732	24,732

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the school and first letter of last name. In panel (a) Year fixed effects are estimated in a first-stage regression without counselor fixed effects. Then these estimates are controlled for in the second stage estimates with counselor fixed effects. In panels (B)-(D) year fixed effects are also included as well as controls for student race and gender. These estimates are clustered at the counselor by year level. The estimates in Panel (B) include controls for counselor experience . Estimates are based on a student's 9th grade counselor.

Table A.26: Predictors of Counselor Value-Added

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Composite Index (6)
(A) Demographics						
White	0.000	0.000	0.000	0.001	0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Female	0.000	0.000	0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
N	3,304	3,304	3,304	3,304	3,304	3,304
(B) Education						
Undergrad In Massachusetts	0.003*	0.003*	0.001	0.001*	0.001	0.004
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Undergrad Selective	0.000	0.000	0.001	0.000	0.002	0.003
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.005)
Master's Highly Selective	-0.001	-0.001	0.004	0.002	0.002	0.018*
	(0.005)	(0.005)	(0.003)	(0.002)	(0.003)	(0.009)
N	770	770	770	770	770	770
(C) Years Experience (9th Grade)						
Novice	0.003*	0.003*	0.003***	0.002***	0.002*	0.007**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Log(Years)	0.001	0.001	0.000	-0.000	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
Former Teacher	-0.001	-0.001	-0.001	-0.000	-0.001	-0.004*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
N	3,304	3,304	3,304	3,304	3,304	3,304
(D) Assigned Students						
Caseload (in 100s)	-0.001	-0.001	-0.001	-0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
N	1,700	1,700	1,700	1,700	1,700	1,700

Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). Observations are counselor year pairs. Estimates are from regressions of counselor's value-added on their characteristics. They include year fixed effects. Estimates of experience effects compute year fixed effects in a two-step process to account collinearity between years of experience and year fixed effects. Estimates in panel (C) are based on years of experience for the 9th grade cohort. 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). 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 A.27: Correlation between Value-Added and Caseload (in 10s of Students)

	Graduate High School (1)	Attend College (2)	Attend College Readiness (3)	College Selectivity (4)	Composite Index (5)	Education Index (6)
(A) No FE						
Caseload (in 10s)	0.00310	0.00321	-0.00199	0.00040	-0.00056	0.00110
	(0.00229)	(0.00238)	(0.00240)	(0.00168)	(0.00216)	(0.00216)
(B) School, Year FE						
Caseload (in 10s)	0.00462	0.00479	-0.00121	0.00243	0.00143	0.00346
	(0.00305)	(0.00317)	(0.00363)	(0.00234)	(0.00306)	(0.00303)

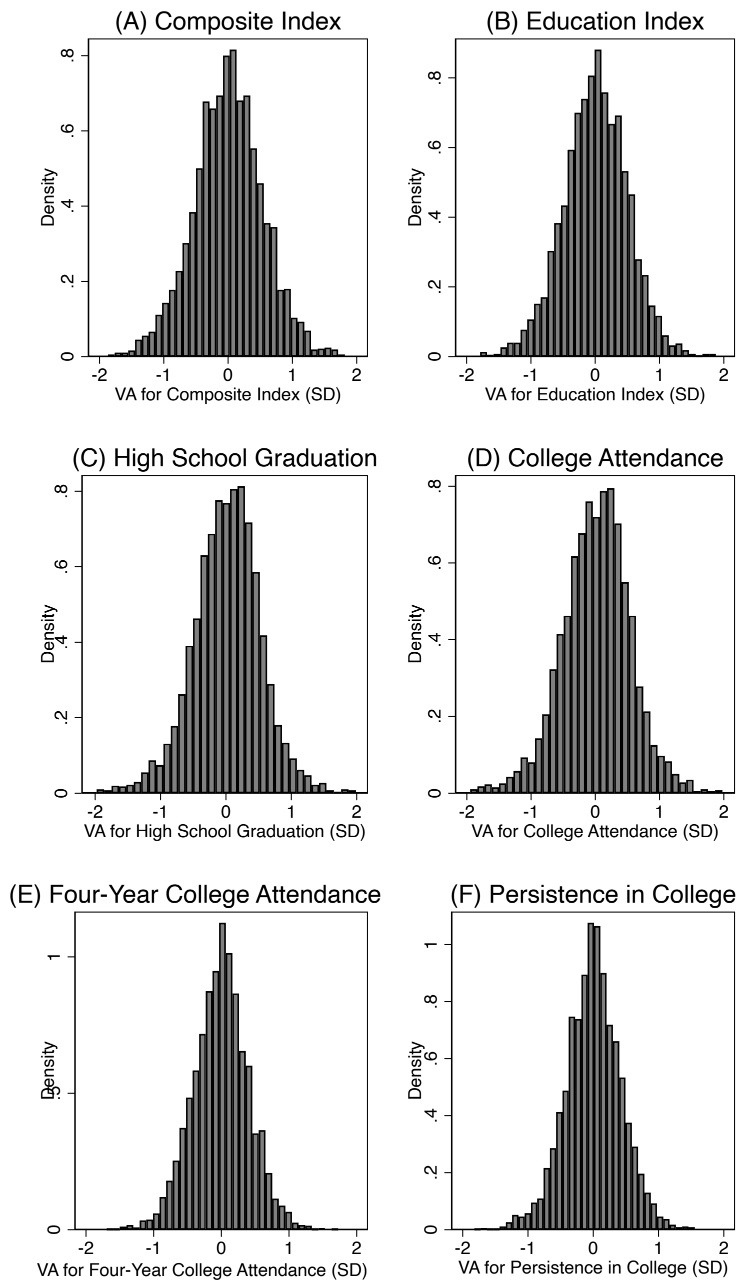
Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. The estimates show the correlation between a counselor's value-added (in the columns) and their caseloads. Caseloads are divided by ten, so the estimates represent the change in value-added associated with a ten student increase in caseloads. Panel A does not include any fixed effects, and panel B conditions on school and year fixed effects. (*p<.10 **p<.05 *** p<.01).

Table A.28: Impact of Caseloads on Counselor Value-Added Sample

	Grade 9 Caseload	Grade 11 Caseload		
	Graduate High School	Attend College	Attend Four-year College	College's Graduation Rate
	(1)	(2)	(3)	(4)
(A) OLS Caseload				
Caseload (in 100s)	-0.030**	-0.018	-0.031*	-0.039**
	(0.012)	(0.011)	(0.015)	(0.013)
(B) Student Controls				
Caseload (in 100s)	-0.013*	-0.002	-0.009	-0.021***
	(0.006)	(0.005)	(0.007)	(0.007)
(C) School, Year FE				
Caseload (in 100s)	-0.003	-0.000	-0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.002)
(D) Within School var. from Num. Counselors				
Caseload (in 100s)	0.001	-0.002	-0.002	-0.006**
	(0.003)	(0.002)	(0.003)	(0.002)
(E) Within School var. from HS Size				
Caseload (in 100s)	-0.012**	-0.007	-0.008*	-0.006**
	(0.004)	(0.004)	(0.004)	(0.002)
(F) Within School var. from Other Gr. Size				
Caseload (in 100s)	-0.015**	-0.007	-0.008	-0.006*
	(0.005)	(0.005)	(0.005)	(0.003)
For High-Achievers	0.012*	0.033***	0.045***	0.030***
	(0.006)	(0.006)	(0.008)	(0.005)
For Low-Achievers	-0.043***	-0.061***	-0.077***	-0.054***
	(0.005)	(0.007)	(0.008)	(0.005)
N	638,974	705,358	705,358	705,358

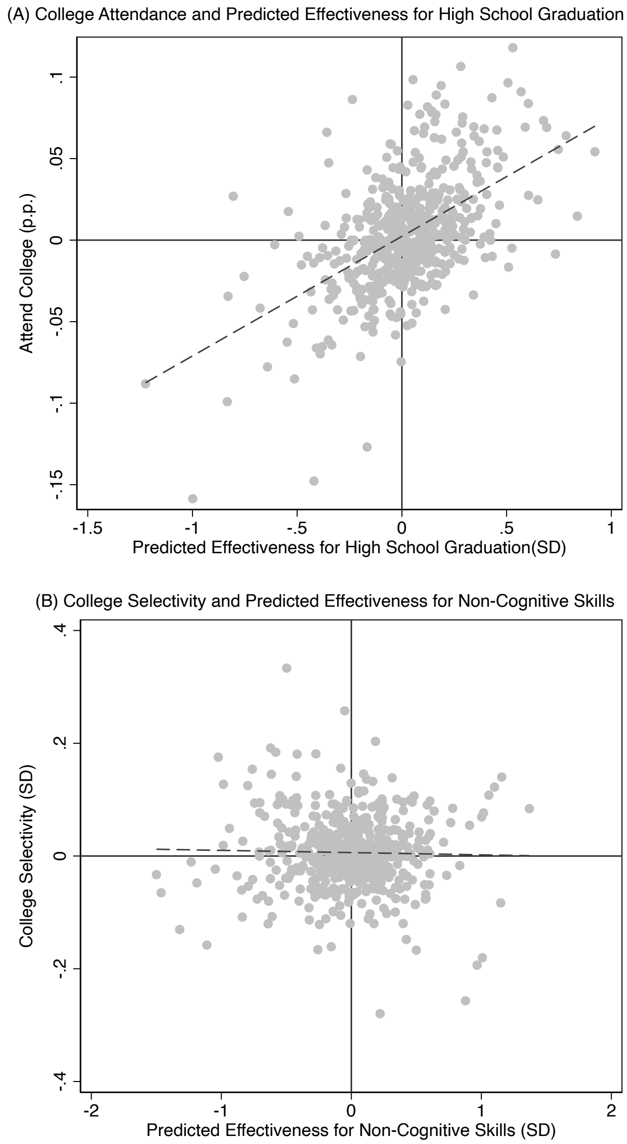
Notes: Heteroskedasticity robust standard errors clustered by school and year are in parentheses. (*p<.10 **p<.05 *** p<.01). The point estimates represent the change in the counselor's value-added associated with a 100 student change in caseloads (or students per counselor). Panel (A) contains estimates 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. The effects are in percentage points. College attendance is based on attendance within six months of finishing high school. College's graduation rate refers to the six-year graduation rate at the college a student attends. College graduation rate is zero for students who do not attend college within six months of finishing high school.

Figure A.1: Distribution of Value-Added



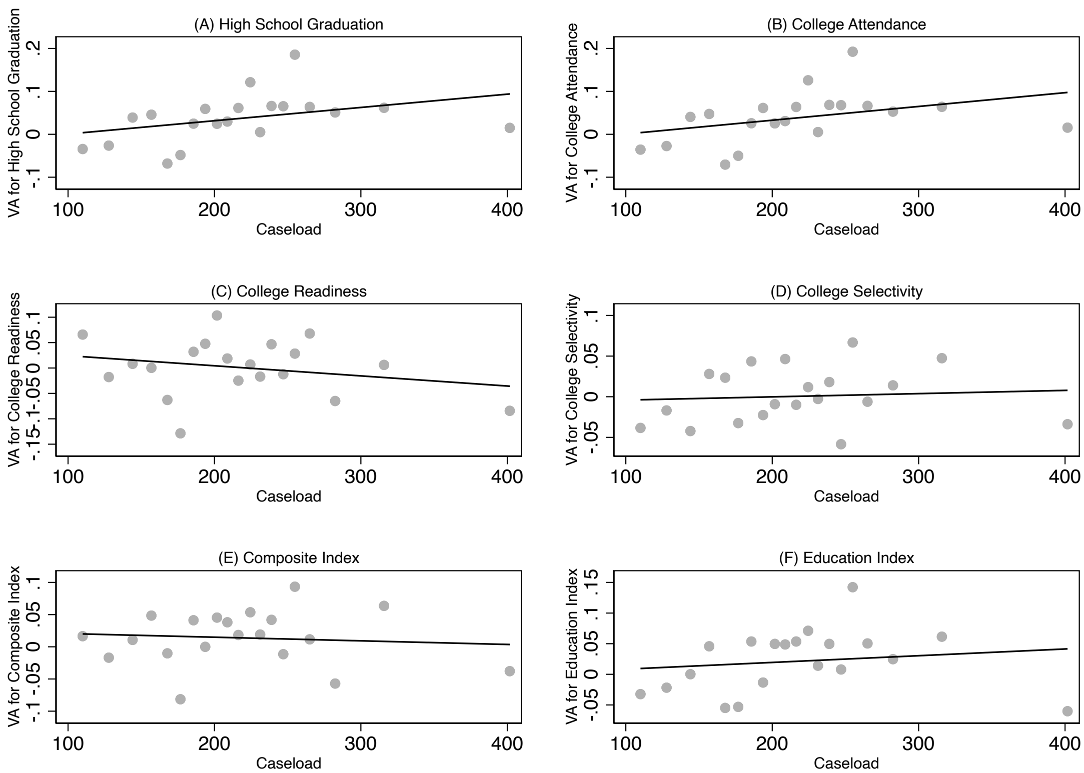
Notes: The figures above show histograms of counselor effects. These are based on empirical Bayes estimates of effectiveness for all students a counselor has served in my sample. Each counselor is represented once. Panels (A) through (E) are in standard deviation units (for the given index). Panels (F)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

Figure A.2: Dimensions of Effectiveness



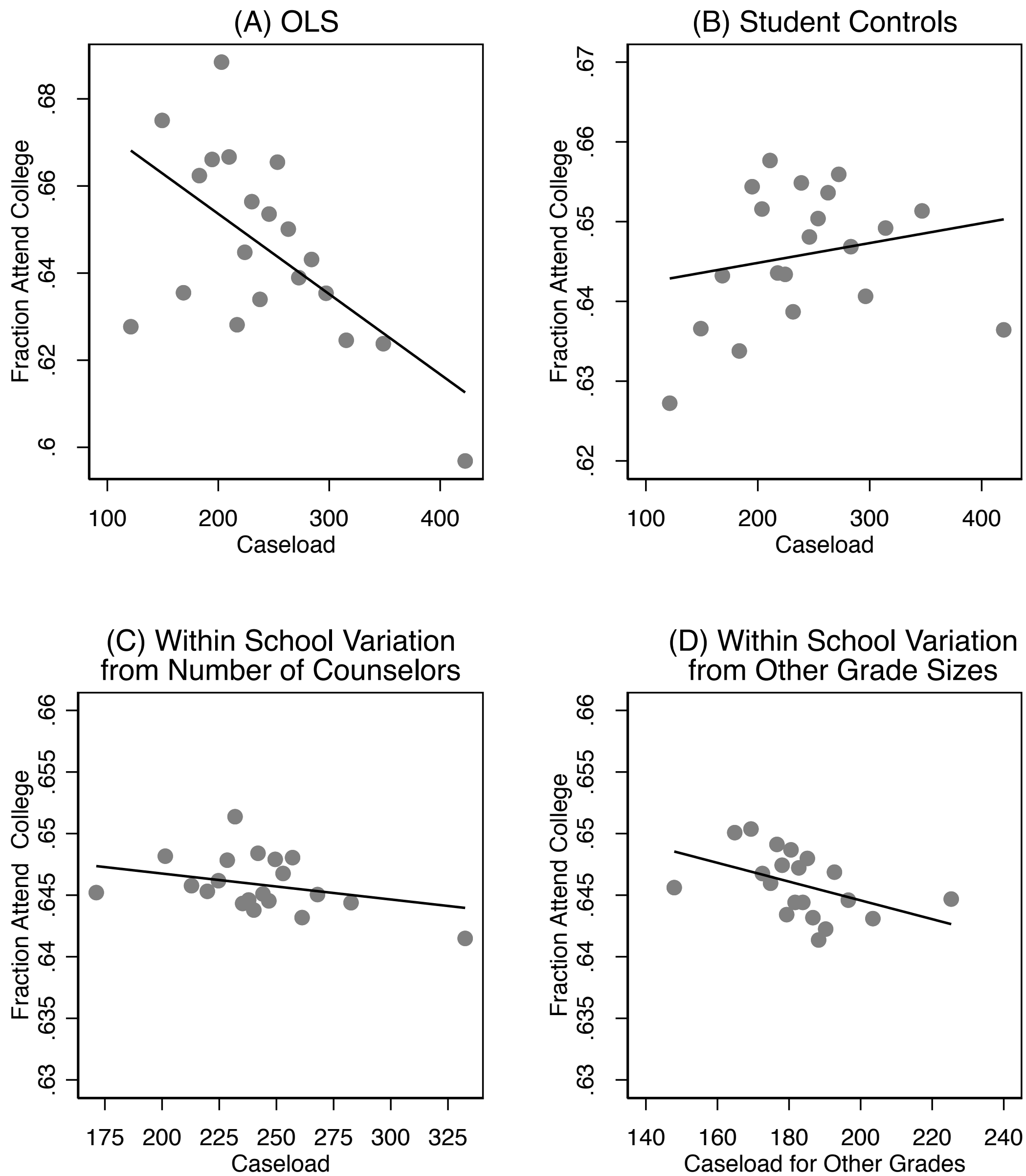
Notes: The figures above show the relationship between counselors' predicted effectiveness in terms of one outcome and their impact on a different outcome. They contain one dot for each counselor. In panel (A), the x-axis represents the counselor's predicted (i.e. leave-year-out) effectiveness in standard deviations for high school graduation. The y-axis indicates the counselor's average impact on 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 coun- selors' predicted effectiveness in terms of high school graduation and 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 A.3: Correlation between Caseloads and Value-Added



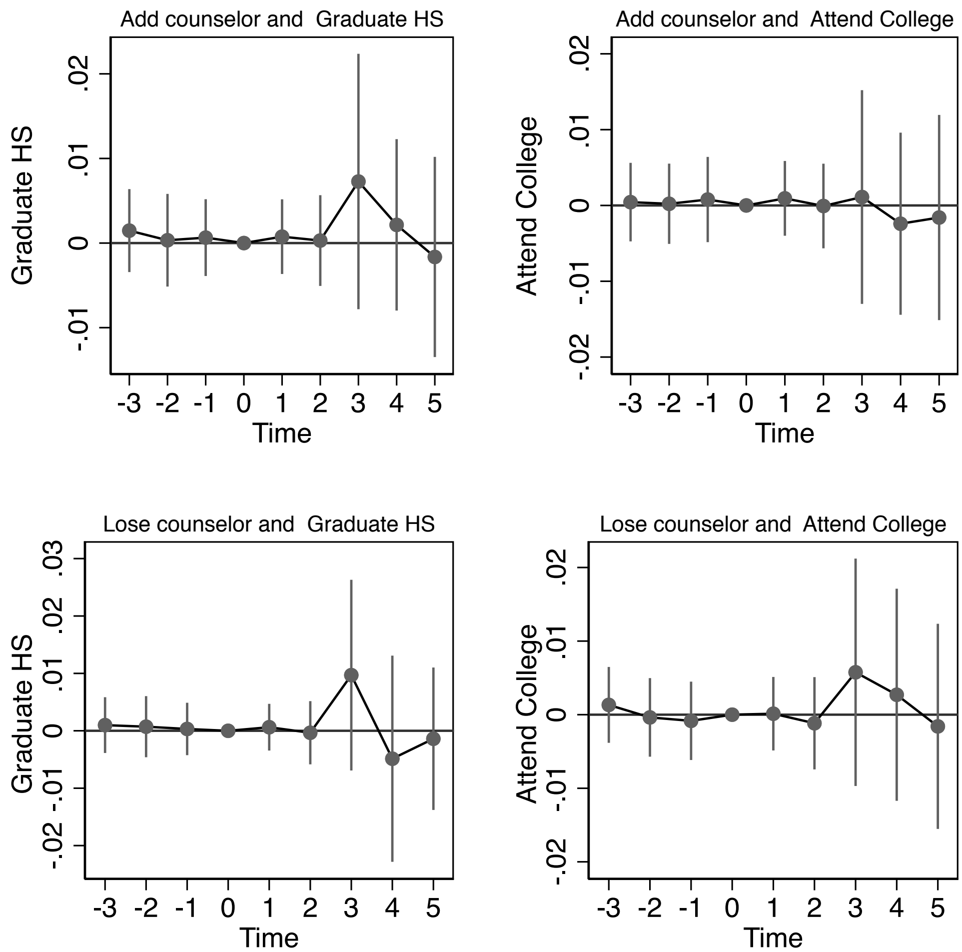
Notes: These figures show the relationship between counselor caseloads and counselor value-added. They include school fixed effects and observations have been binned into twenty groups (of equal size). None of the relationships are statistically significant at the 1% level. They are based on the six value-added measures listed in each subfigure title and counselors who have between 100 and 500 students per year. I use leave-year-out value-added estimates so the same students are not represented in both the dependent and independent variables. Caseload estimates are based on the number of students estimated to fall within a counselor's assignment range based on student last names. Thus they may contain some measurement error. Observations are at the counselor level.

Figure A.4: Relationship between Caseloads and 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' 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.

Figure A.5: 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.

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 their 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 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 Index	College Readiness	College Selectivity	Education Index	Highly Selective
(A) Overall						
Composite Index	0.574	0.358	0.286	0.277	0.239	0.404
(B) Relative to Indiv. VA						
Non-Cognitive	0.000					
Cognitive skills	0.667	0.000				
College Readiness	0.659	0.477	0.000			
College Selectivity	0.644	0.357	0.394	0.000		
Education Index	0.660	0.410	0.370	0.293	0.000	
Highly Selective Coll	0.601	0.368	0.437	0.236	0.400	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. Estimates are based on the first counselor to which a student is quasi-randomly assigned. Highly selective college is an indicator for whether the student attends a highly selective college as defined by Barron's 2009 rankings.

C Results from Wake County North Carolina

C.1 Summary of Results

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 a third the size of the Massachusetts sample and not all of the same outcome measures are available.

Table C.1 shows the variance in student outcomes due to counselors.[67] In Wake County, the standard deviation of counselor effects on high school graduation is 5.9 percentage points and it is 3.1 percentage points for college enrollment. Table C.2 indicates similar effects when student outcomes are regressed on their counselor's predicted value-added.[68] Table C.3 shows that counselor effects are similar across student achievement levels, gender and race.[69]

The Wake County estimates are larger than those from Massachusetts, but also noisier. They are noisier in part because the Wake County sample is much smaller. They may be larger than those from Massachusetts because the Wake County sample is more diverse and has lower baseline levels of achievement. The Wake County estimates are also similar to those from the specifications which reweight my Massachusetts estimates to be representative of the state population (Table A.5). Thus, my main estimates from Massachusetts may understate counselor effects in the broader US population.

In addition, Wake County provided data on principals' evaluations of counselors 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 more than one year of data. North Carolina Principals evaluate counselors on a scale of 0 to 4 and 3 is the most common score.

Figure C.2 shows that counselors' evaluation scores are not predictive of student outcomes - though I have limited power to rule out moderate effect sizes. In fact, the correlation coefficients in Table C.4 are all negative.[70] Scatterplots in Figure C.3 also indicate little relation between a counselor's average evaluation score and their students' high school graduation and college attendance rates.[71]

These correlations indicate that evaluations may pick up on different skills than the effects I measure. However, the results are noisy so they should be interpreted with caution. The items on the evaluation rubric are 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 the outcomes for which I construct value-added scores, I expected the sections on supporting student success to lead to total evaluation scores more highly (and positively) correlated with educational attainment. Overall, this analysis indicates that current evaluation tools may not be especially effective at identifying counselors who impact students' educational attainment, which is consistent with research on principal evaluations of teachers (Jacob & Lefgren, 2008). Furthermore, Table C.5 shows that experience is not positively related to counselor effects.

[67] 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.

[68] Figure C.1 shows the main placebo tests and predictive validity tests for Wake County.

[69] Income data are not available from Wake County.

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

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

Novice counselors have larger impacts and the coefficient on years of experience is negative. New tools may be needed if schools wish to identify the most effective counselors or target professional development to counselors who most need guidance on increasing educational attainment.

Finally, Wake County provided information on sibling pairs which can be used to conduct an additional validation test. For this, I identify siblings assigned to different counselors and regress the difference in student outcomes on the difference in their counselor's value-added. These tests are based on 2,985 students with a sibling assigned to a different counselor. They indicate that a one standard deviation change in counselor value-added is associated with a 1.16 SD increase in the student's educational attainment index. The confidence interval includes one, so these estimates provide a nice validation of the value-added estimates.

C.2 Tables and Figures

Table C.1: Wake County Standard Deviations of Counselor Effects

	Covariance Approach (1)	CFR Approach (2)
Education Index	0.100	0.112
High School Graduation	0.059	0.064
College Attendance	0.031	0.036
Four-Year College Attendance	0.036	0.043
College's Graduation Rate	0.018	0.023
Persistence in College	0.059	0.062

Notes: Column 1 shows estimates of the standard deviation of counselor effects based on the covariance of individual counselor effects over time. Column 2 shows estimates based on the approach for computing the variance of teacher (or counselor) effects in Chetty, Friedman and Rockoff (2014a).

Table C.2: Wake County Predicted Counselor Effectiveness (in SDs) and Educational Attainment

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) Overall Effects						
Education Index	0.064***	0.035***	0.042***	0.020***	0.064***	0.115***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
(B) Outcome-Specific Measure						
Value-Added	0.064***	0.036***	0.044***	0.023***	0.066***	0.115***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)
N	88,690	88,690	88,690	88,690	80,338	88,690

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based on the first counselor to which a student is quasi-randomly assigned in Wake County, North Carolina. Estimates also contain controls for the student's 8th grade test scores, English language proficiency, special education receipt, enrollment in 8th grade in an Wake County 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 columns 6 and 7 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. College's graduation rate refers to the six-year graduation rate at the college a student attends. College graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table C.3: Wake County Impact of Predicted Counselor Effectiveness by Student Characteristics

	Graduate High School (1)	Attend College (2)	Attend Four-Year College (3)	College's Graduation Rate (4)	Persist 1st Year (5)	Education Index (6)
(A) By Prior Achievement						
Low Achievers	0.051***	0.030***	0.036***	0.018***	0.051***	0.095***
	(0.008)	(0.004)	(0.005)	(0.003)	(0.008)	(0.012)
High Achievers	0.052***	0.038***	0.045***	0.026***	0.054***	0.110***
	(0.006)	(0.004)	(0.005)	(0.003)	(0.007)	(0.011)
P-value Difference	0.95	0.18	0.15	0.80	0.07	0.35
Low Achiever Mean	0.84	0.60	0.41	0.31	0.27	0.19
High Achiever Mean	0.76	0.57	0.44	0.33	0.31	0.12
(B) By Gender						
Male	0.050***	0.039***	0.043***	0.022***	0.053***	0.107***
	(0.006)	(0.004)	(0.005)	(0.003)	(0.006)	(0.010)
Female	0.054***	0.031***	0.040***	0.023***	0.051***	0.101***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.006)	(0.010)
P-value Difference	0.46	0.15	0.55	0.69	0.64	0.55
Male Mean	0.77	0.55	0.38	0.26	0.28	0.06
Female Mean	0.82	0.62	0.47	0.32	0.35	0.24
(C) By Race						
Non-White	0.058***	0.039***	0.044***	0.023***	0.054***	0.115***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.007)	(0.011)
White	0.046***	0.031***	0.039***	0.022***	0.051***	0.094***
	(0.007)	(0.005)	(0.006)	(0.004)	(0.007)	(0.013)
P-value Difference	0.13	0.29	0.51	0.67	0.86	0.23
Non-white Mean	0.72	0.45	0.30	0.23	0.20	-0.11
White Mean	0.86	0.69	0.53	0.39	0.38	0.38

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include fixed effects for the first letter of the student's last name, each school, grade and year (when a student was first assigned to the counselor). Estimates are based 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, enrollment in 8th grade in a Wake County 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 test students and those below average are referred to as low test students. Panel (B) shows estimates separately by gender. Panel (C) divides students by whether or not their race/ethnicity is reported as white. Counselor effectiveness is defined using the composite index of effectiveness.

Table C.4: Correlation of Value-Added & Observation Ratings in Wake County

	Value-Added Measures				
	Education Index (1)	Graduate High School (2)	Attend College (3)	Attend Four-year College (4)	Historical Graduation Graduation Rate (5)
VA Graduate High School	0.939	1			
VA Attend College	0.925	0.772	1		
VA Attend Four-Year College	0.944	0.806	0.892	1	
VA Historical Graduation Rate	0.797	0.584	0.836	0.918	1
Average Evaluation Rating	-0.0207	0.0369	-0.0290	-0.0657	-0.0905

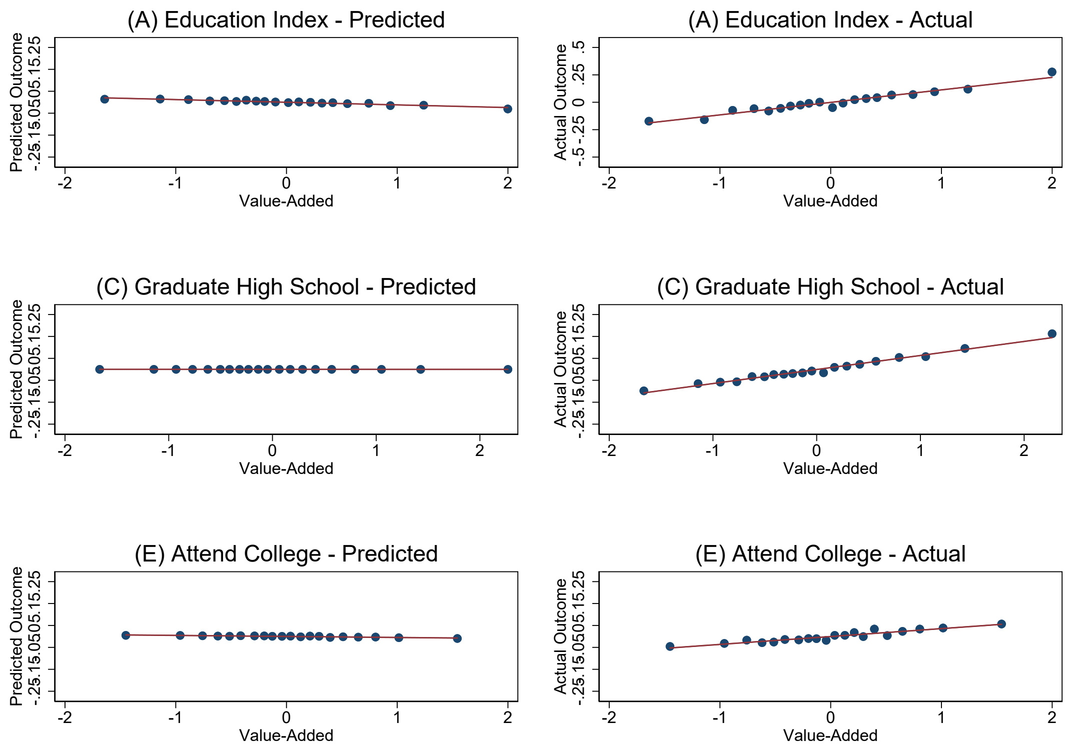
The above estimates are the correlations of each counselor's value-added (in Wake County, NC) and their average evaluation rating. Average evaluation ratings are only used for counselors evaluated in at least two years between 2015 and 2018 (to improve the validity of these measures). 53 counselors have evaluation ratings in at least two years and value-added estimates (based on three cohorts of students). 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. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rates are zero for students who do not attend college within six months of finishing high school.

Table C.5: Impact of Counselor Characteristics in Wake County

	Graduate High School (1)	Attend College (2)	Attend Four-Year (3)	Persist 1st Yr (4)	Education Index (5)
(A) Race Match					
Race Match	-0.003	0.002	0.005	-0.004	0.004
	(0.007)	(0.008)	(0.008)	(0.006)	(0.017)
Non-White Match	-0.002	0.004	0.007	-0.002	0.007
	(0.009)	(0.010)	(0.010)	(0.008)	(0.022)
White Match	-0.004	0.002	0.005	-0.006	0.003
	(0.007)	(0.008)	(0.009)	(0.006)	(0.018)
(A) Gender Match					
Gender Match	0.000	-0.009**	-0.007*	-0.011***	-0.013
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)
Female Match	0.003	-0.005	0.003	-0.005	0.000
	(0.006)	(0.007)	(0.007)	(0.005)	(0.013)
Male Match	-0.002	-0.014**	-0.017***	-0.019***	-0.027**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.011)
(B)Educator Experience					
Novice Counselor	0.020***	0.022***	0.021***	0.020***	0.051***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.013)
Log(Years Counselor)	-0.024***	-0.024***	-0.026***	-0.019***	-0.060***
	(0.006)	(0.008)	(0.007)	(0.006)	(0.016)
Log(Years Educator)	-0.021***	-0.019***	-0.015***	-0.018***	-0.044***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.012)

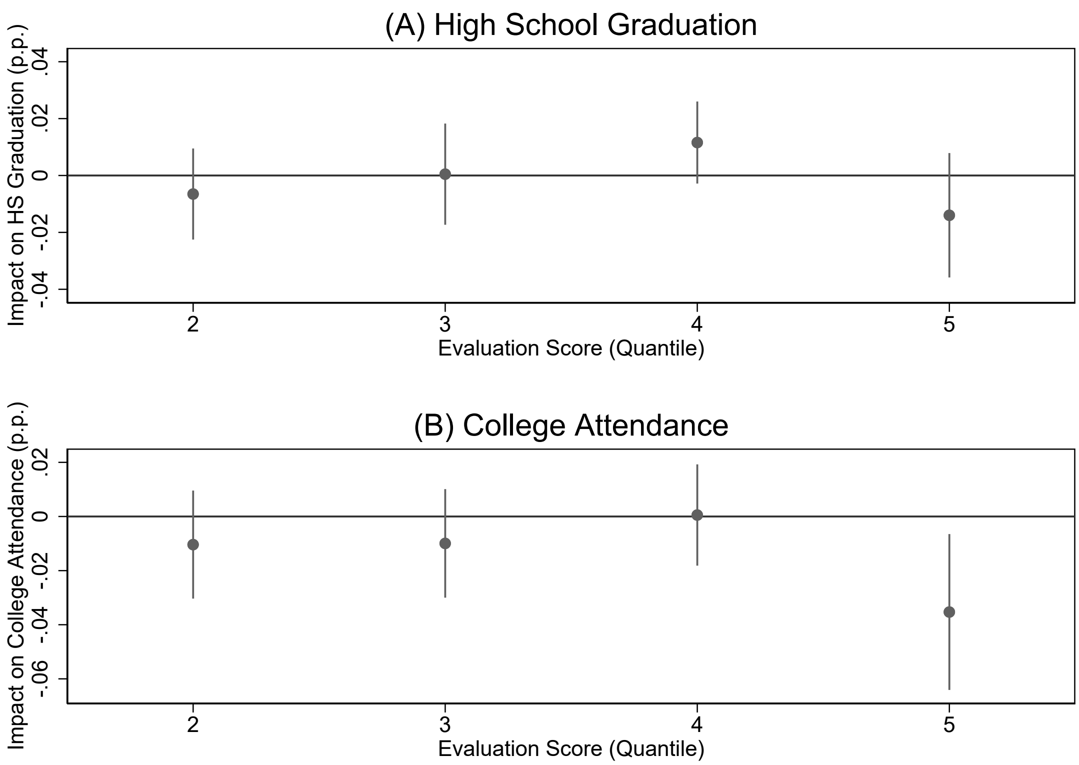
Notes: Heteroskedasticity robust standard errors clustered by counselor in parentheses. (*p<.10 **p<.05 *** p<.01). All regressions include letter of last name, school, cohort and grade fixed effects students' race, gender, achievement, attendance, and average income levels at the school. Estimates are based on a student's first assigned high school counselor in Wake County, North Carolina. Race Match specific refers to Black students being assigned to Black counselors, and similarly for Hispanic or Asian counselors and students. Experience is based on years of experience in Wake County when the student is first assigned the counselor.

Figure C.1: Effects of Counselor Value-Added on Predicted and Actual Outcomes in Wake County



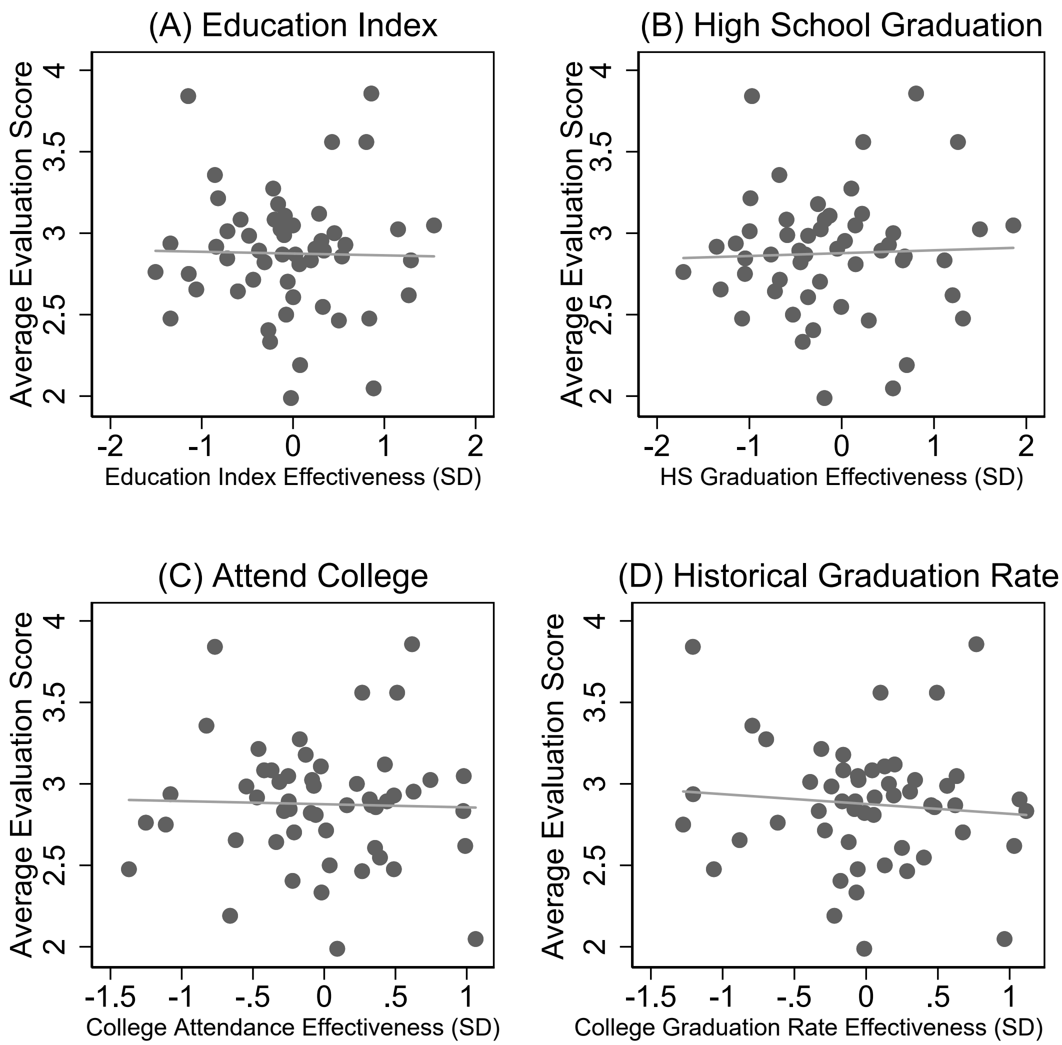
Notes: The figures above show binscatters of counselor value-added and students predicted and actual outcomes in Wake County, NC. The figures on the left show students' predicted outcomes based on their seventh grade test scores. The figures on the right show students actual outcomes. Both predicted and actual outcomes are 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. In each graph, the y-axis indicates students' predicted or actual outcome (Panels (A) and (B) are for the composite index, panels (C) and (D) for high school graduation, and panels (E) and (F) for four-year college attendance). Estimates are all The x-axis is based on counselors leave-year-out empirical Bayes estimates of effectiveness. The lines are from regressions of the residualized outcomes on counselor value-added. There are the same number of students in each bin. The relationship between counselor value-added and predicted effects is not significant at the 10% level in any of the figures on the left. Conversely, the relationship between value-added and actual outcomes is significant at the 1% level for all figures on the right, and each of the confidence interval for each of these coefficients contains 1. Table 3 contains the estimates corresponding to these figures.

Figure C.2: 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 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 their 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 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. 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 C.3: 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.