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

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Abstract

Counselors are a common school resource for students navigating complicated and consequential education choices. I estimate counselors' causal effects using quasi-random assignment policies in Massachusetts. Counselors vary substantially in their effectiveness at increasing high school graduation and college attendance, selectivity, and persistence. Counselor effects on educational attainment are similar in magnitude to teacher effects, but they flow through improved information and assistance 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). School counselors may play a valuable role in this process, but there is currently no rigorous evidence on their impacts.

Most high schools employ school 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 school counselors since it is the term preferred by the profession. Historically, and in my sample, these types of counselors are often referred to as guidance counselors.

[2] In 2017, the national ratio was one secondary school counselor per 237 students, but this may understate school counselor caseloads since it includes multiple types of counselors (Common Core of Education Data, 2017). Survey data indicate that the average high school caseload is 286 students (Clinedinst & Patel, 2018).

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

This paper provides the first quantitative evidence on the causal effects of individual high school 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 the 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 graduation and college attendance rates, and significant but

[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 **??** contains an example of the assignment rules.

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. Counselors' effects on college readiness and selectivity are most predictive of educational attainment. 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. Other observable characteristics and experience, however, are not very predictive of effectiveness.

Fifth, I provide evidence that the benefits, in terms of educational attainment, from improving access to effective counselors may 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.[5] Nevertheless, we do not know how to increase counselor effectiveness, or if there may be benefits to larger caseload reductions. Thus, more research is needed on how to identify effective counselors or improve their efectiveness. Finally, increasing access to effective counselors will also likely have effects similar to many successful college-going interventions and to increasing teacher effectiveness.

Broadly, this paper builds on three literatures. First, and most directly, it is related to research on counselors in other settings, such as 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, 2022; 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.

This paper provides the first quantitative evidence on how much individual high school counselors impact students and predictors of counselor effectiveness. 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 limited effects on college enrollment and persistence (Barr & Castleman, 2019; Castleman & Goodman, 2018; Castleman, Page & Schooley, 2014; Sullivan, Castleman & Bettinger, 2021; Bettinger & Evans, 2019; Gurantz et al., 2020). The only papers to estimate the effectiveness of individual counselors are focused on different settings and based on fewer than forty counselors (Barr & Castleman, 2021; Canaan et al., 2022). Barr & Castleman (2021) find little variation in effectiveness among counselors at an after-school program, perhaps because the counselors follow a very

[5]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.

standardized protocol, while Canaan et al., (2022) find more variation among 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., 2022; 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 of the benefits of improvements 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 elementary and high school teachers suggests that counselors are an important part of the education production function (Chetty, Friedman, & Rockoff, 2014b; Jackson, 2018).[6] At a high

[6] 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, 2023) 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 difficult to identify the effects of 11th and 12th grade teachers and I do not have data on MA high school teachers. Furthermore, these comparisons are challenging because most estimates of teacher value-added likely understate teachers' full effects on educational attainment (Chamberlain, 2013).

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 **??** describes counselors' roles and a theoretical framework. Section **??** describes the data and section **??** presents the methods. Section **??** shows the impacts of assignment to a more effective counselor. Section **??** examines which observable characteristics predict counselor effectiveness and section **??** examines the importance of counselor's caseloads and how the main results compare to estimates of teacher effects. Section **??** concludes.

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).[7] Given these

[7]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

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 traditional value-added models (e.g., Todd & Wolpin, 2003) 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 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 guid-

they are consistent with the survey data and reports from the state on which I am focused.

ance 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 are accepted into college (Hoxby & Turner, 2013; Bulman, 2015; Clinedinst & Koranteng, 2017). In addition, counselors may help students complete applications or forms, which can impact 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).[8]

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 through their impacts on students' accumulated academic achievement (Chamberlain, 2013; Jackson, 2018; Todd & Wolpin, 2003; Canaan et al., 2022). Existing models, however, do not capture potential effects of educators 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 educators influence educational attainment to incorporate effects on student awareness of long-term options and direct influence on the barriers students face in accessing education and labor market opportunities.

I treat the first two mechanisms in section **??** 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,

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

and the steps needed to reach them.[9] 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.[10]

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

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

[9]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.

[10]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.

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.[11] 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. 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 impor-

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

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

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

Previous studies model educator effects on Y_l only through the academic achievement dimension ($\beta_l \alpha_{ij}$). This means the model implicitly assumes $E[\omega_{kij}]\Gamma_l = 0$ and $E[\omega_{dij}]\delta_l = 0$.[12] 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 **??** 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 schooler to a counselor based on their last name. They typically

[12] Meaning educators either have no effects on the other dimensions or those dimensions are irrelevant to Y_l

involve dividing a cohort of students among the school's N counselors by alphabetically sorting students' last names and then equally dividing the names across the number of counselors in the school so 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 **??** 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 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.

[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.

[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.

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 **??** 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, while others assigned students to counselors by grade, tracks or programs, and some schools only had one counselor.[16] I restrict my sample to the 146 schools with last name assignment rules posted for at least three cohorts. Table A.2 compares the schools in my sample to all high schools in the state. Suburban 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.

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

[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 school counselor and a separate college counselor.

[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.

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) to Human Resources (HR) data on counselors' employment, education, and demographics. Table **??** describes the counselors in my sample, the HR data, and the 20% of counselors who self-reported their education data. In section **??**, 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 **??** 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 **??** 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 **??** indicates that the students matched to counselors are slightly less diverse and higher achieving than the average Massachusetts student. Some of the positive selection could be driven by higher resource schools having nicer websites with easy to find assignment rules. In addition, many high schools have separate counselors for students with limited English proficiency or those in career and technical education. This means these students are frequently excluded from 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

[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.

[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.

2012. Bachelor's degree completion rates are only for cohorts prior to 2015, and college persistence rates are not available for the 2019 cohort.

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 school 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.[23]The state also has a formal evaluation process.

Some U.S. high schools have college counselors who are separate from school 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 school counselors, or to assign them to students based on students' last names (Clinedinst & Patel, 2018). The effects of school counselors on educational attainment may be 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 **??** 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,

[23]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.

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 in the teacher literature (Chetty, Friedman & Rockoff, 2014a). I compare outcomes of 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 Figure **??** example where a student with last name Daugherty would be assigned Mr. Carty if in the class of 2009 but Mr. Jalowayski if in the class of 2010. Second, I use variation in assignments due to student names. This includes variation from the example where a student named Kane would be assigned Mr. Jalowayski in 2009 but one named King would be assigned Ms. Shapiro. I also use variation across letters, e.g., comparing a student named Cary to one named Dunn at the same school, conditional on average differences in C and D students (based on statewide letter fixed effects).[24]

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. Because of the school fixed effects, my estimates do not capture information sharing or spillover effects in schools, so I likely underestimate counselors' full effects. The letter fixed effects subtract off statewide differences common to 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 independent of counselor assignment. To further alleviate concerns of student sorting, and following the teacher literature, I control for students' eighth grade test scores, demographic indicators, and indicators

[24]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.

of services received in eighth grade.[25] The controls for race/ethnicity are important for addressing the non-random distribution of last names for some racial/ethnic groups across the alphabet. The other controls are primarily included to improve power. As described in section **??**, I use this approach to estimate value-added following the methods from Chetty, Friedman & Rockoff (2014a). Figure **??** and Table **??** 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 in the example, 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.

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.

[25] The full set of controls includes race/ethnicity, gender, English learner status, receipt of services for special education, title 1 services, a 504 plan, free or reduced price lunch, eighth grade attendance, enrollment in a Massachusetts public school in 8th grade, eighth grade test scores 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 measures from eighth grade since counselors may affect access to services in high school.

$$Y_i = \mu_j + \beta X_i + \nu_n + \delta_s + \gamma_g + \psi_t + \epsilon_i \quad (6)$$

Then, I compute the student residuals as

$$\hat{Y}_i = Y_i - (\hat{\beta} X_i + \hat{\nu_n} + \hat{\delta}_s + \hat{\gamma_g} + \hat{\psi}_t) \quad (7)$$

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

$$\hat{\mu}_{jt} = \Phi \bar{Y}_j^{-t} \quad (8)$$

where Φ is the vector of coefficients from regressing $\bar{Y}_t$ on $\bar{Y}_j^{-t}$.[26] 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 a stationary process.[27] Under stationarity, 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 (i.e. counselor-year combinations) with a time span s of up to 3 years between them to estimate σ_{Ys}.[28] Figure A.1 plots the autocorrelations

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

[27] Formally, $E[\mu_{jt}|t] = E[\epsilon_i|t] = 0$, cov$(\mu_{jt}, \mu_{j,t+s}) = \sigma_{\mu s}$, 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.

[28] Figure A.1 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.

for my main outcomes. They are largest for the composite index of effectiveness and are quite stable over time for all estimates. Figure A.2 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.[29] 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 **??** 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 **??** 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.[30] 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 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, $\hat{\mu}_{jt}$, for a variety of high school and college outcomes. Table A.6 shows the correlations of these outcomes. Since counselors may impact many

[29] 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.

[30] These estimates indicate the relationship between student outcomes and assignment to a counselor whose value-added is predicted to be one standard deviation above average. The estimates in Table **??** 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.

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.[31]

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 indices for cognitive and non-cognitive skills map directly to the mechanisms for counselor effects described in section **??** and are similar to indices used in Petek & Pope (2023) and Jackson (2018). The college readiness and selectivity indices are related to the information and direct assistance mechanisms. They capture outcomes such as SAT taking and college selectivity which are likely to be influenced by the information a counselor provides about college options or application assistance.[32] I use these indices to test the model from section **??**. The fifth index captures counselors' direct effects on educational attainment. Finally, I create a composite measure of effectiveness based on all five 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.

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

[31] 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.

[32] College selectivity is defined using Barron's 2009 selectivity ratings (Barron's Educational Series, College Division 2008). Following Chetty et al. (2017) I define selective schools as those in Barron's tiers 1-5 and highly selective as those in Barron's tiers 1-2.

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.[33]

I use the main tests in Chetty, Friedman & Rockoff (2014a) to examine forecast bias and predictive validity, plus a regression discontinuity design to test the validity of my approach. It is important to note that my models differ 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, 2023; Naven, 2020). Furthermore, the counselor setting is advantageous because we know how counselors are assigned and can condition on the assignment mechanism.[34]

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-added. This forecast bias test provides an estimate of the proportion of variation in value-added that comes from sorting on unobserved achievement. Figure **??** and Table **??** 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 **??** are all less than 4%, indicating that selection bias is not a significant issue.[35] This is also consistent with the large literature on teachers suggesting that

[33]Table A.7 shows that student and counselor characteristics are not significant predictors of counselors' caseloads.

[34]This may make selection on observables more plausible than in the teacher setting, where researchers approximate the assignment process with selection on observables. Any selection bias here 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.

[35]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 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 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.

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.[36] Figure **??** and Table **??** show these results, and Figure **??** 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 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.[37]. 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

[36]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.

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

are clustered by student and counselor since students will have repeated observations.

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

Figure **??** 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. Table A.9 explores the sensitivity of these tests to using value-added estimates that control for different sets of baseline controls or fixed effects. It 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.[38] 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 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 observe how students are assigned and control for it, and I find no evidence of sorting conditional on these controls, the selection on observables assumption seems reasonable here. 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.[39]

[38] 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.

[39] Appendix B contains an additional validity test based on sibling pairs in Wake County. This shows that, on average,

5 Counselor Effectiveness

5.1 Main Results

Figure **??** 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.[40]

Tables **??** and **??** 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 (pp) more likely to persist between a first and second year of college and 1.2 pp 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 pp 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 degree. 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.[41]

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.[42] Table A.12 also shows

the difference in siblings' outcomes can be predicted by the difference in their counselors' value-added.

[40] 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 of the tables report results for the composite index and outcome-based value-added measures, and the estimates are similar across measures.

[41] 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).

[42] 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.

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 (if we assume the marginal students whose college choices are influenced by their counselor experiences the average change in earnings associated with the college). 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 Tables **??** and **??** also show 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 pp. 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 predictors of the relevant and related outcomes.[43] 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 Tables **??** and **??** is based on the four short-term dimensions of counselor effects described in sections **??** and **??**. 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.

[43]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.

Table **??** shows the estimated variance of counselor effects. These are similar in magnitude to the estimates reported in Tables **??** and **??**, and estimates based on the RD design (Tables **??** and **??**) are also similar.

5.2 Differences across Subgroups

Counselor effects are largest for low-achieving students.[44] Panel (A) of Figure **??** 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 0.0 8pp and 1.6 pp for high achieving students on those outcomes. Table **??** 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.

Counselor effectiveness also matters more for low-income students' high school graduation than for high-income students. For most other outcomes, counselor effects do not significantly vary across income groups. In addition, among low-income students, counselors are most important for lower achieving students (Table A.14). Table **??** 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 by student gender (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.

Counselors' large effects on low-income and low-achieving students are important because

[44] Low-achieving refers to students with 8th grade test scores below the state average, while high achievers have above average test scores. Low-income is defined as students who received free or reduced-price lunch in 8th grade.

these students are most likely to be on the margin of completing high school and attending college. Low-income students are also less likely to have access to social networks with college information and other resources to help them access college (Hoxby & Avery, 2013). Furthermore, these students, and their parents, may be less likely to seek additional support to compensate for or supplement the counselor's role if assigned a less effective counselor. These results indicate that counselors may be an important resource for closing socioeconomic gaps in education.

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, and for the lower-income students in these schools (Table A.16). Most other effects do not significantly vary across school poverty measures or school accountability levels. Table A.17 also shows that counselors with smaller caseloads have larger impacts on high school graduation and college attendance, but differences for other outcomes are not significant.[45]

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.18 shows the effects of a counselor's value-added for the specific group on outcomes for that same group. Nearly all of the estimates in this table are larger than the average effects reported in Tables **??** and **??**, 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.19 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

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

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 **??**. The cognitive and non-cognitive skills indices map directly to the mechanisms from section **??**. 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 **??**, 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 **??** reports the variation in counselor effects on these indices and Table **??** shows that counselor effectiveness on these indices predicts the relevant outcomes.

Figure **??** 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 **??** shows that for most outcomes, effectiveness in terms of cognitive and non-cognitive skills are not significantly related to educational attainment.[46] Furthermore, Table A.20 indicates that counselor effects on the courses students take in

[46]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

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 **??** by showing that counselors influence educational attainment by doing more than just affecting short-term skill development. Counselor effects on cognitive and non-cognitive skills appear unrelated to their effects on educational attainment.[47] 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. Counselors' impacts on SAT taking is significantly related to their effect on college attendance. 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.

Finally, it is important to note that these estimates cannot capture all potential mechanisms for counselors effects. For instance, spillover effects across students or counselors within a school will not be captured becasue of the school fixed effects.

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.21). 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.

Tables **??** and **??** show how counselors' predicted effectiveness on various dimensions relate to

since all four value-added estimates are included in the regressions. Tables **??** and **??** show the estimates when each value-added measure is independently used in a regression.

[47] This is true for the non-cognitive skills index when I regress student outcomes on the indices one at a time in Table **??**, 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.

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 pp 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.3 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.3 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.3 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 Tables **??** and **??** are positive and statistically significant, indicating that most counselors who are good on one dimension are also good on other dimensions. These positive correlations may simply pick up on counselor effort, since counselors who work hard on one dimension may be more likely to work hard and thus appear better on all dimensions. However, a full test of the reasons for these corelations is beyond the scope of this paper. Finally I do not find much evidence of specialization, where counselors focus only on certain outcomes or students at the expense of others (Appendix C).

5.5 Robustness Checks

Next, I show that my results are robust to alternate approaches. First, I examine the importance of the imputed counselor assignments. Tables A.3 and A.4 show the results are similar when I drop observations with imputed assignments. This table also explores sensitivity across the different reasons for imputation. Table A.22 also shows estimates based on a logit specification for binary outcomes, and Table A.23 shows results from the RDD specification for additional outcomes.

Second, I follow the approach from Miller, Shenhav, & Grosz (2021) to reweight my sample so the results represent the magnitudes expected for the full population of Massachusetts public high schoolers. This approach reweights the identifying sample to be representative of the state's high schoolers and then calculates effect sizes for this reweighted population. These results indicate that the average effect of counselors on all Massachusetts high schoolers is likely larger than my main estimates (Table A.5). 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 teh results' external validity 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 B 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

Next, 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 regress student outcomes, Y_i, on measures of counselor characteristics, and control for the first letter of the student's last name, cohort, school and grade fixed effects, as well as the student's academic achievement and demographics.[48] The coefficients I report indicate how being assigned to a counselor of a certain type is causally linked to a student's outcome. These estimates may not indicate the causal effect of a counselor's education or demographics on the student, since these characteristics may be correlated with a counselor's unobservable characteristics, and these analyses are exploratory so they should be interpreted with caution. Nevertheless, these predictors may be useful for school administrators deciding who to hire or how to match students to counselors.

Overall, it is difficult to predict which counselors are effective based on observables. Figure A.4 and Table **??** summarize the main observable characteristics that I examine. The strongest predictor of student outcomes is the racial match of students and counselors.

Table **??** indicates that students are roughly two percentage points more likely to graduate high school and persist in college if assigned a counselor from the same racial group relative to one from a different race. Since there are relatively few non-white counselors, the next row of Table **??** looks more generally at the effects of non-white students being matched to a non-white counselor.[49] They indicate that non-white students are 2.8 pp more likely to graduate high school and 3.3 pp more likely to persist in college if matched to a non-white counselor, relative to 1.7 pp and 2.0 pp for white students matched to a white counselor. The benefits of being matched to a same-race counselor are even larger when looking specifically at black students matched to black counselors. There is no detectable benefit from being matched to a counselor of the same gender (Table D.1).[50]

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, similar counselors may know more about the unique hurdles that URM students face and colleges which may be a good fit. Research on teachers also indicates that URM educators may serve as role models (Dee, 2005;

[48] Appendix D contains more details on the estimates presented here.

[49] Sixty-two percent of non-white counselors are Black, 21 percent are Hispanic, and 12 percent are Asian. There are too few Asian and Hispanic counselors to break out results separately for them.

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

Gershenson et al., 2022). 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.

Table **??** also shows that counselors who have a bachelor's degree from a college in Massachusetts tend to be more effective, though most other measures of counselors' educational experiences are not significant predictors. More details on the how counselors' education experiences relate to their effectiveness are describe in Appendix D.

In addition, most measures of counselor experience are not positively related to student outcomes. Counselors with teaching licenses have students with slightly lower educational attainment (Table D.1), and years of experience are not positively related to student outcomes. Appendix D descibes the details for how I estimate returns to experience and additional results.

Finally, I examine how counselors' characteristics relate to their value-added (Table D.2.[51] Value-added is not significantly related to race, gender, caseload, the counselor's education, or years of experience. The only significant predictor is being a novice counselor.

7 Comparisons to Caseloads and Teacher Effects

Next, I examine the importance of counselors' caseloads for student outcomes and how they compare to the impacts of counselor effectiveness. I also discuss the similarity in magnitude of counselors' and teachers' effects on high school graduation and college attendance.

[51]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.

7.1 Caseloads

Counselors typically serve many students, and many schools in the U.S. have caseloads well above the 250 student caseload recommended by the American School Counselor 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. College enrollment rates are highest at schools with smaller caseloads, but this relationship is insignificant and nearly flat when I control for student achievement and demographics or school and year fixed effects (Figure E.1. Thus, the true relationship between caseloads and student outcomes may be small. To address caseload endogeneity, I use five approaches to measure how caseloads relate to educational attainment in Massachusetts high schools. These approaches, and variation in results across them, are summarized in Appendix E. The approaches use a mix of controls for student and school characteristics, as well as variation within schools over time in the number of students or counselors. Table **??** summarizes the results across the different approaches.

Here, I focus on the estimates based on within school variation in caseloads due to the number of students in other grades.[52] These results, in Panel (F) of Table **??**, indicate that a 100 student decline in the number of students (in grades other than that of student i) is associated with a 1.6 pp increase in high school graduation rates. On average, hiring a new counselor in a Massachusetts high school would reduce full caseloads by 74 students and the number of students a counselor serves in other grades by 46 students. Thus, these estimates suggest that, on average, hiring a new counselor would increase high school graduation rates by approximately 0.8 percentage points.

Table **??** 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 coun-

[52]These are arguably the most robust and they are the largest estimates so they provide a conservative upper bound.

selor caseloads and high school graduation, college attendance, and four-year college attendance.[53]

Overall, the results suggest that caseloads are probably negatively related to educational attainment, however, 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, and my estimates are identified on relatively small fluctuations around the status quo. There may be larger returns to reducing caseloads in places with much larger caseloads or in places with many low-achieving students since I find 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.[54] For instance, counselors may not change their general approach to counseling because they have a smaller caseload in one year, but they may make more permanent or larger changes if there were a larger longer-term shift in caseloads.

Caseloads may also matter for outcomes, such as mental health, which I cannot measure with my data. Finally, technological advances may make caseloads less important. Counselors can email many students at once, and 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. Nevertheless, hiring more counselors may be much simpler than hiring more effective counselors or improving the effectiveness of counselors.

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

[53] The same pattern is not evident for low-income students.
[54] The standard deviation of within school variation in other grade caseload sizes is 27 students.

to 8th grade teacher, as measured by test scores, increases college attendance by 0.8 pp. 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 not well captured by test scores. Teachers in high school may also have larger effects on postsecondary education than elementary school teachers (Petek & Pope, 2023).

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 as measured by non-cognitive outcomes and test scores.[55] Jackson's largest estimates suggest that a one standard deviation better teacher increases high school graduation by 1.5 pp and four-year college intentions by 1.1 pp. These estimates are slightly smaller than my estimates for high school graduation and 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 (2023) 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 pp and reduce high school dropout by 0.5 pp. They find slightly larger benefits to focusing on improving behavior value-added, which is projected to improve SAT taking by 8.4 pp and high school dropout rates by 5.9 pp. 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 educators 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.

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

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.[56] 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 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

[56] 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).

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.[57] 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 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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[57]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.

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10 Tables and Figures

Figure 1: Example Assignment Rules

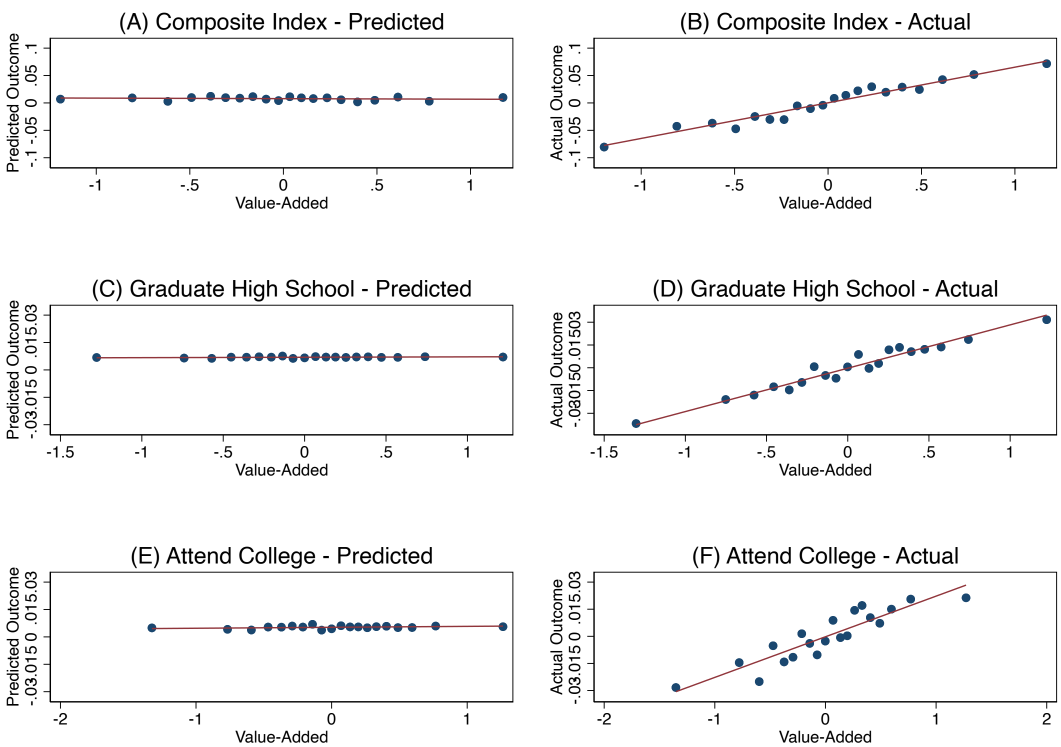
Canton High School
Guidance Department

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

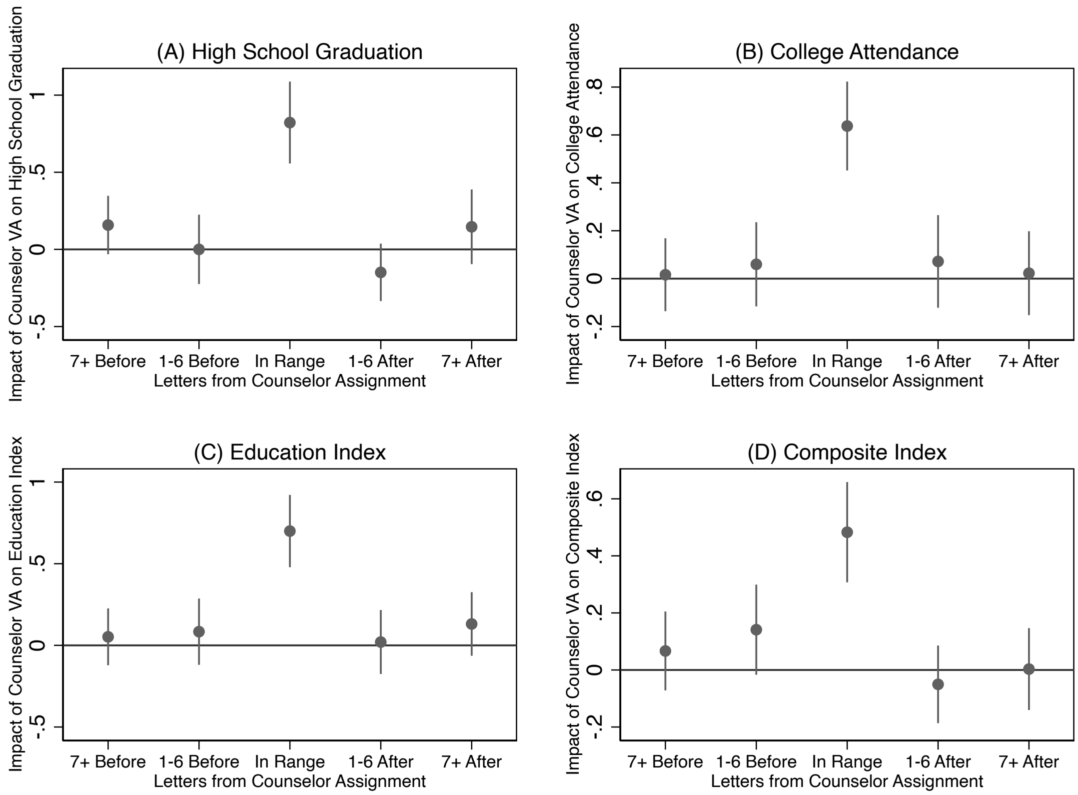
Notes: Above is an example of the assignment rules for Canton high school in 2009. The columns refer to the graduating class - e.g. 12th graders will be the graduating class of 2009 while 9th graders are the graduating class of 2012. Rules vary across these four cohorts because of changes in the distribution 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



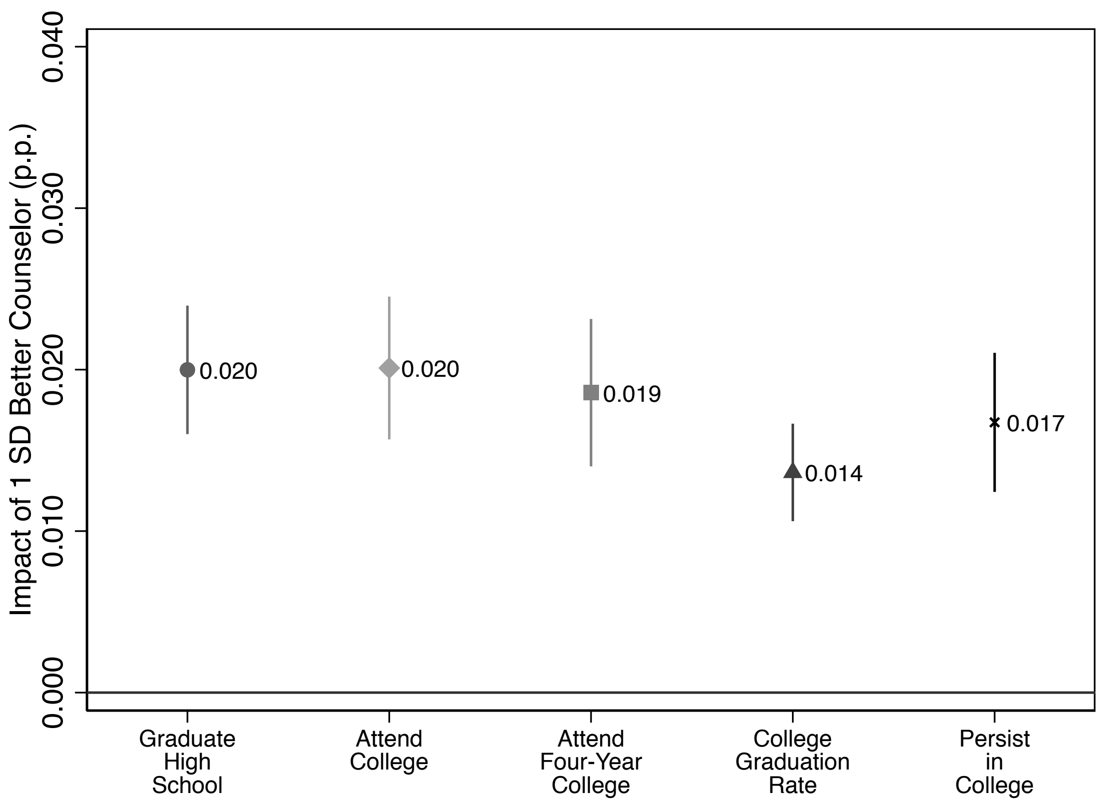
Notes: The figures above show binscatters of counselor value-added and students predicted and actual outcomes. The figures on the left show students' predicted outcomes based on their seventh grade test scores. The figures on the right show students actual outcomes. Both predicted and actual outcomes 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 **??** contains the estimates corresponding to these figures.

Figure 3: Coarse Regression Discontinuity Design



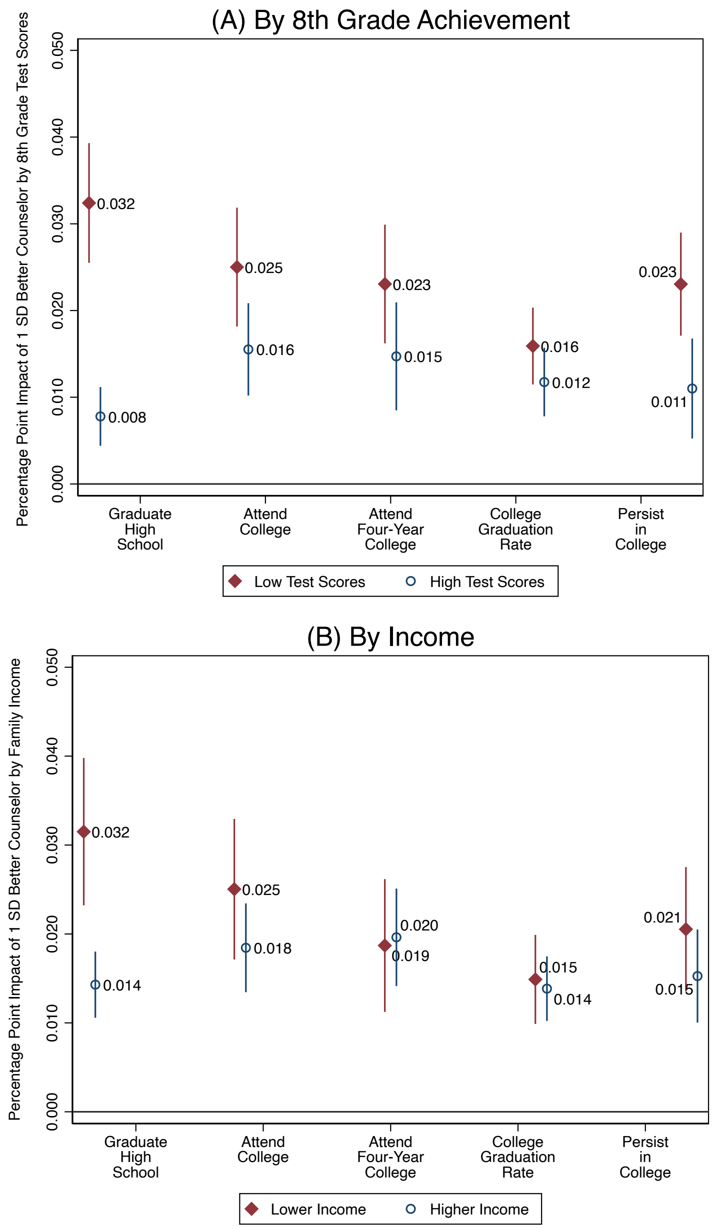
Notes: These figures show the relationship between counselor value-added (measured using the composite index) and student outcomes by students' distance (in terms of letters) to the counselor's assignment window. Since students are assigned to counselors based on the first letter(s) of their last name, 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 4: Impact of a One Standard Deviation Improvement in Counselor Effectiveness



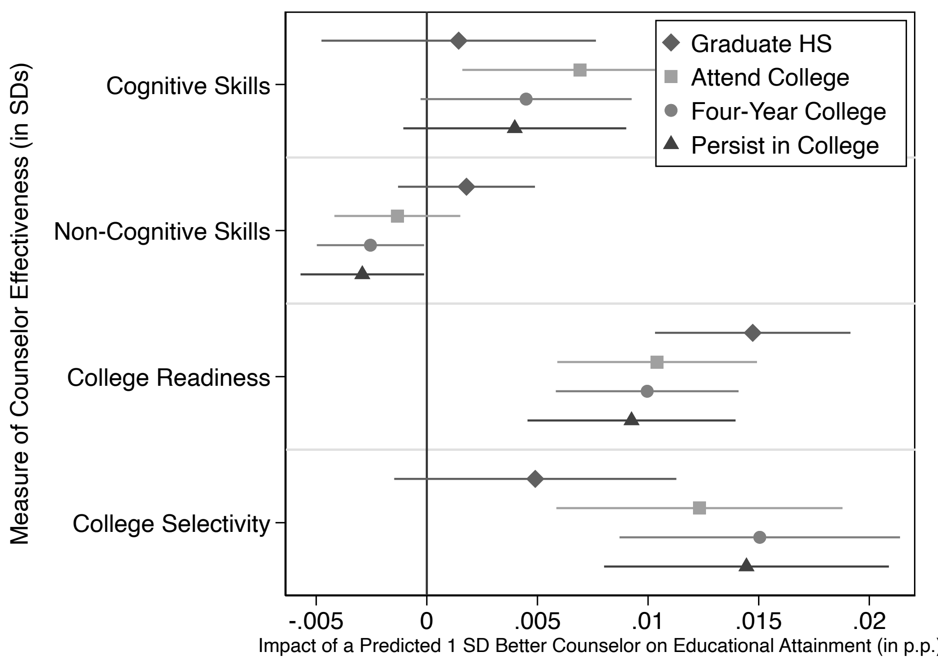
Notes: This figure shows the relationship between student outcomes and the counselor's predicted effectiveness in terms of that same outcome. The coefficients indicate the benefit of assignment to a counselor who is one standard deviation above average relative to an average counselor (as measured by 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 5: 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 6: 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.

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: This table summarizes the characteristics of the counselors in my sample. Column 1 contains all counselors in the HR records who worked in a high school. Column 2 contains all counselors in column 1 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: VA Sample	Match to Counselor: In HR Sample	Match to Counselor: Ed Sample	Caseload 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: This table summarizes the characteristics of the student in my sample and how they compare to the average characteristics of Massachusetts high schoolers. Column 1 is based on all students in a MA high school who were projected to graduate between 2008 and 2019. Column 2 is based on 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 value-added 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 (and all scores have been converted to this 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 (which I define as a tier 1 or tier 2 school in the Barron's 2009 rankings). Persist 1st Year is an indicator for whether a student persists between their first and second years of college. It is not available for the 2019 cohort. BA is an indicator for earning a Bachelor' degree within five years of starting college. It is not available for the 2016-2019 cohorts. All remaining outcomes represent the fraction of students in the sample achieving that outcome.

Table 3: Validity of Value-Added Estimates

	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). These estimates indicate the extent to which value-added is correlated with predicted versus actual outcomes. 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: This table shows the estimated standard deviations of counselor effects based on a few different approaches. Columns 1, 3 and 5 show estimates of the standard deviation of counselor effects based on the covariance of individual counselor effects over time ($Cov(\mu_{jt}, \mu_{j,t-1})$. 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/ethnicity (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 5A: Measures of Predicted Effectiveness and Student Outcomes

	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)
(A) Effectiveness for Overall Indices						
Composite Index	0.020***	0.020***	0.019***	0.014***	0.017***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Education Index	0.024***	0.025***	0.020***	0.014***	0.022***	0.016***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
(B) Effectiveness for Education						
Graduate High School	0.027***	0.022***	0.014***	0.010***	0.017***	0.014***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Attend College	0.026***	0.021***	0.014***	0.010***	0.016***	0.013***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Attend Four-Year	0.014***	0.020***	0.020***	0.014***	0.020***	0.013***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Graduation Rate	0.013***	0.017***	0.019***	0.014***	0.017***	0.012***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Persist 1st Year	0.019***	0.024***	0.019***	0.012***	0.020***	0.014***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Bachelor's Degree	0.021***	0.022***	0.017***	0.011***	0.018***	0.010*
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.006)
(C) Effectiveness for SR Indices						
Cognitive Skills	0.007**	0.014***	0.013***	0.007***	0.012***	0.004
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Non-Cognitive Skills	0.004**	-0.000	-0.001	0.000	-0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College Readiness	0.016***	0.013***	0.013***	0.011***	0.012***	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
College Quality	0.014***	0.021***	0.023***	0.017***	0.021***	0.012***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
N	224,563	224,563	224,563	224,563	201,834	128,542

Notes: Heteroskedasticity robust standard errors clustered by counselor are in parentheses. (*p<.10 **p<.05 *** p<.01). The coefficients indicate the impact of assignment to a counselor who is predicted to be one standard deviation above average on the relevant metric. Each row is a separate regression, so that each row shows the independent relationship between one value-added measure and the outcome described in the column header. The estimates are based on the leave-year-out estimates of counselor value-added. In Panel (A), value-added is measured using the composite index (which captures counselors' effects on multiple domains) or the education index. Panel (B) is based on outcome-specific value-added measures. For instance, the first row of panel (B) shows how a counselor's value-added for high school graduation specifically relates to different student outcomes. Panel (C) contains results based on four different (and mutually exclusive) indices of counselor effectiveness. The composite index is based on the four indices in panel (C) and the education index. The effects are in percentage points. 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. 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 5B: Measures of Predicted Effectiveness and Indices of Student Outcomes

	Cognitive Skills (1)	Non-Cognitive Skills (2)	College Readiness (3)	College Selectivity (4)
(A) Effectiveness for Overall Indices				
Composite Index	0.019***	0.069***	0.071***	0.037***
	(0.006)	(0.009)	(0.007)	(0.005)
Education Index	0.023***	0.010	0.057***	0.039***
	(0.005)	(0.009)	(0.006)	(0.005)
(B) Effectiveness for Education				
Graduate High School	0.013**	0.026***	0.057***	0.027***
	(0.005)	(0.010)	(0.006)	(0.004)
Attend College	0.013**	0.025***	0.055***	0.026***
	(0.005)	(0.010)	(0.006)	(0.004)
Attend Four-Year	0.022***	-0.006	0.051***	0.041***
	(0.006)	(0.010)	(0.008)	(0.006)
Graduation Rate	0.015***	0.005	0.058***	0.041***
	(0.006)	(0.010)	(0.008)	(0.006)
Persist 1st Year	0.022***	-0.006	0.040***	0.038***
	(0.005)	(0.010)	(0.008)	(0.005)
Bachelor's Degree	0.008	0.023	0.032**	0.029***
	(0.009)	(0.017)	(0.013)	(0.009)
(C) Effectiveness for SR Indices				
Cognitive Skills	0.057***	-0.037***	0.012	0.027***
	(0.007)	(0.012)	(0.008)	(0.005)
Non-Cognitive Skills	-0.013***	0.105***	0.020***	-0.002
	(0.004)	(0.004)	(0.004)	(0.003)
College Readiness	0.000	0.042***	0.068***	0.026***
	(0.005)	(0.008)	(0.007)	(0.004)
College Quality	0.028***	-0.005	0.059***	0.048***
	(0.007)	(0.010)	(0.008)	(0.007)
N	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). The coefficients indicate the impact of assignment to a counselor who is predicted to be one standard deviation above average on the relevant metric. Each row is a separate regression, so that each row shows the independent relationship between one value-added measure and the outcome described in the column header. The estimates are based on the leave-year-out estimates of counselor value-added. In Panel (A), value-added is measured using the composite index (which captures counselors' effects on multiple domains) or the education index. Panel (B) is based on outcome-specific value-added measures. For instance, the first row of panel (B) shows how a counselor's value-added for high school graduation specifically relates to different student outcomes. Panel (C) contains results based on four different (and mutually exclusive) indices of counselor effectiveness. The composite index is based on the four indices in panel (C) and the education index. The effects are in standard deviation units (of the relevant index). 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 6A: Regression Discontinuity Estimates of Counselor Effects by Letters to Assignment Ranges for Student Outcomes

	Graduate High School (1)	Attend College (2)	Four-Year College (3)	Graduation Rate (4)	Persist 1st Year (5)
(A) Composite VA					
7+ Before	0.004**	0.001	0.001	0.001	0.004
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
1-6 Before	-0.001	0.003	0.005*	0.003*	0.004
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
In Range	0.016***	0.013***	0.010***	0.005***	0.012***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
1-6 After	-0.002	0.002	0.002	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
7+ After	0.002	0.002	-0.003	-0.001	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
(B) Outcome-specific VA					
7+ Before	0.004	0.000	-0.000	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
1-6 Before	0.000	0.001	0.005	0.003	0.000
	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)
In Range	0.021***	0.016***	0.014***	0.007***	0.011***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
1-6 After	-0.004	0.002	0.002	-0.001	0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
7+ After	0.004	0.001	0.004	0.001	-0.001
	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)
N	519,028	519,028	519,028	519,028	456,944

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). This table shows how the relationship between a counselor's predicted value-added and student outcomes as one moves from last names outside the counselor's assignment window, to those in-range (i.e. assigned to that counselor) and then out of the assignment window. 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. 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. Effect sizes are in percentage points. 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 6B: Regression Discontinuity Estimates of Counselor Effects by Letters to Assignment Ranges for Indices of Outcomes

	Cognitive Skills (1)	Non-Cognitive Skills (2)	College Readiness (3)	College Selectivity (4)
(A) Composite VA				
7+ Before	0.000	0.003	0.007	-0.002
	(0.004)	(0.003)	(0.005)	(0.005)
1-6 Before	0.006*	-0.001	0.007	0.011**
	(0.004)	(0.004)	(0.006)	(0.006)
In Range	0.012***	0.009**	0.034***	0.016***
	(0.003)	(0.004)	(0.005)	(0.005)
1-6 After	-0.003	-0.007	-0.000	-0.003
	(0.003)	(0.004)	(0.004)	(0.005)
7+ After	0.001	-0.005	0.000	0.002
	(0.004)	(0.004)	(0.005)	(0.005)
(B) Outcome-specific VA				
7+ Before	0.001	0.006**	0.013***	-0.005
	(0.005)	(0.003)	(0.005)	(0.007)
1-6 Before	0.005	0.000	0.014**	0.007
	(0.005)	(0.003)	(0.006)	(0.008)
In Range	0.021***	0.014**	0.038***	0.019**
	(0.004)	(0.006)	(0.005)	(0.008)
1-6 After	-0.004	-0.003	0.004	-0.011*
	(0.004)	(0.003)	(0.005)	(0.006)
7+ After	0.003	-0.002	-0.000	0.006
	(0.005)	(0.003)	(0.005)	(0.007)
N	519,028	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). This table shows how the relationship between a counselor's predicted value-added and student outcomes as one moves from last names outside the counselor's assignment window, to those in-range (i.e. assigned to that counselor) and then out of the assignment window. 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. 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. Effect sizes are in standard deviations. 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.

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). This table shows how the relationship between a counselor's predicted (leave-year-out) value-added and student outcomes varies by student characteristics. 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.) Panel (C) divides students by whether they are white or non-white. Counselor effectiveness is defined using the composite index of effectiveness (in SDs). The coefficients reported are those from the interaction of the relevant subgroup (e.g., Low Inc) with counselor value-added. Within each panel and column, both coefficients are estimated in one regression. The p-value reports the statistical significance of the difference between the two groups in the panel. 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 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). This table shows the relationship between a counselor's predicted (leave-year-out) value-added and their students' outcomes. The coefficients indicate the impact of assignment to a counselor who is predicted to be one standard deviation above average on the relevant metric. In Panel (A), value-added is measured using the composite index (which captures counselors' effects on multiple domains). Panel (B) contains results based on four different (and mutually exclusive) indices of counselor effectiveness. For each column, the estimates in panel (B) are from one regression which includes all four value-added measures. Panel (C) is based on value-added in terms of the education index. Regressions for panels A, B and C are fit separately. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). 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. 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	0.020***	0.015*	0.007	-0.000	0.017**	0.020
	(0.006)	(0.009)	(0.008)	(0.006)	(0.008)	(0.016)
Race Match: Non-White	0.028**	0.018*	0.015	0.004	0.033***	0.037
	(0.012)	(0.011)	(0.011)	(0.009)	(0.012)	(0.023)
Race Match: White	0.017***	0.018**	0.011	0.004	0.020**	0.034*
	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)	(0.019)
Race Match: Black	0.044***	0.027**	-0.007	-0.025*	0.026	-0.059**
	(0.012)	(0.013)	(0.012)	(0.013)	(0.022)	(0.025)
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)
Highly Selective	-0.005	-0.003	-0.006	-0.005	0.004	-0.007
	(0.005)	(0.008)	(0.009)	(0.005)	(0.009)	(0.016)
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 are in parentheses. (*p<.10 **p<.05 *** p<.01). These estimates indicate the relationship between a counselor's observable characteristic or experience and the student outcome in the relevant column. Each row (and column) is a separate regression. 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. The coefficients indicate the causal relationship between being assigned to a counselor with the noted characteristic and student outcomes, but not necessarily the causal effect of the characteristic/experience itself. In panel (A), race match is defined as assignment to a counselor of the same broad race/ethnicity category: white, Asian, Hispanic or Black. The other race-match rows focus on matches just for non-white students, white students, or black students respectively. Non-white match refers to whether non-white students are matched to another non-white counselor. White match refers to whether white students are matched to a white counselor and matches for black students are similarly defined. 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. Novice is an indicator for being in one's first year as a Massachusetts counselor. Log(years) refers to the natural log of one plus the number of years for which a counselor has worked as a counselor in Massachusetts (since the HR data began in 2008). Panel (C) is based on the counselor's years of experience as of a student's 9th grade year. The effects in columns 1-5 are in percentage points. Those in column 6 are in standard deviation units (of the education index). College attendance is based on attendance within six months of completing high school. Persistence is an indicator for enrolling in a second year of college. Historical graduation rate refers to the six-year graduation rate at the college a student attends. Historical graduation rate and persistence are zero for students who do not attend college within six months of finishing high school.

Table 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 presented here indicate the change in student outcomes 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) include 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.