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Estimating Causal Impacts of School Counselors With Regression Discontinuity Designs

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This article presents a causal regression discontinuity framework for quantifying the impact of high school counselors on students' education outcomes. To demonstrate this method, the authors used data from the National Center for Education Statistics' Schools and Staffing Survey (SASS). Using high school counselor staffing counts and 4-year college-going rates collected through the SASS, the authors found that an additional high school counselor is predicted to induce a 10 percentage point increase in 4-year college enrollment.

Keywords: regression discontinuity, high school counselors

School counselors play a crucial role in U.S. high schools, helping students traverse the challenges of high school and providing insight into the many options available to them following graduation. School counselors supplement teachers by relieving them of guidance duties—a skill set that teachers may not have developed fully through their training or may not have the capacity to implement effectively given their competing demands. The responsibilities of high school teachers are well defined and relatively consistent across schools: They are generally responsible for transferring subject-specific knowledge to their students and enhancing students' abilities to think critically. By contrast, the role of the high school counselor varies greatly across schools and even within schools (Bridgeland & Bruce, 2011; Paisley & McMahon, 2001). Due diligence by the counselor requires a nimbleness and an ability to work with students on an extremely wide range of issues running the gamut from college and financial aid application completion to course work directives to the resolution of behavioral and personal problems.

The typical American high school, by many accounts, is not equipped to provide students with the many and diverse resources that simply cannot be offered by teachers alone. Recent budget cuts have led to mass layoffs of counselors across many districts, particularly in California (Po, 2012). When financial resources are strained and districts are cornered into dismissing staff, the choice of which staff to terminate is challenging. One is compelled to wonder: What is the motivation for honing in on counselors as more dispensable than other staff? Perhaps the lack of causal empirical evidence on the impact of counselors on student outcomes is to blame.

Given the laserlike focus on teachers in the educational research arena, the dearth of rigorous empirical studies on the extent to which school counselors influence student outcomes is not surprising. In this article, we use an empirical approach to estimate the impact of an additional counselor on student outcomes, and we provide an example of how this approach might be used with 4-year college-going as an outcome of interest. Many states (e.g., Alabama, Louisiana, Montana, New Hampshire, Vermont) specify that a high school must increase the size of the counseling staff when the school enrollment exceeds an established threshold. This means that similar high schools may have dramatically different student-to-counselor ratios depending on whether their enrollment just exceeds or just falls short of the threshold beyond which an additional school counselor must be added. Such laws provide ideal settings for studies geared toward drawing causal inferences through a regression discontinuity design. We demonstrate how to use this empirical technique with counselor staffing and 4-year college-going data from the Schools and Staffing Survey (SASS), which is administered by the National Center for Education Statistics (NCES).

Background

The recent wave of research on teacher evaluation and accountability is tremendously important and long overdue (Clotfelter, Ladd, & Vigdor, 2006; Glazerman et al., 2010; Goldhaber, 2007; Goldhaber & Brewer, 1997; Jacob & Lefgren, 2008; Rivkin, Hanushek, & Kain, 2005). However, the disproportionate focus on teachers in the school accountability and school quality research creates the illusion that teachers are solely responsible for the success or failure of American schools and the students within them. With growing evidence of the impact of teacher quality on a variety of student outcomes, the importance of a strong teaching force is clearly a powerful driver of student success (Darling-

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Hammond, 2000; Greenwald, Hedges, & Laine, 1996). But teachers alone cannot shoulder the entire burden of ensuring that students reach their full potential, nor can they take sole responsibility for preparing students for life after high school. The research agenda around school counselors might be best developed by following the path of research literature around teachers, which first tackled the importance of quantity and has now segued into the thornier territory of quality.

Empirical Studies on the Impact of School Counselors

Only recently have researchers begun using rigorous empirical techniques to evaluate the impact of school counselors on student outcomes. Carey and Harrington (2010a, 2010b) analyzed data from the School Counseling Program Implementation Survey by using stepwise hierarchical linear regression and controlling for important school-level demographic characteristics to determine that lower student-to-counselor ratios in Utah were associated with increased attendance rates (a result also found in Nebraska) and decreases in the frequency of disciplinary actions in the state. Examining the postsecondary outcomes of 1,305 highly qualified students from seven high schools in a large urban district, Pham and Keenan (2011) estimated that a 1% decrease in the first-generation student-to-counselor ratio is associated with a 0.4% decrease in the odds of bypassing 4-year college enrollment. Pham and Keenan used the methodological technique of logistic regression, controlling for students' grade point average and demographic characteristics.

In statistical modeling, controlling for variables that are likely related to both the outcome and the predictors of interest achieves the goal of whittling bias from the parameter estimates of interest. If it were possible to control for every single observable and unobservable characteristic related to the outcome (e.g., 4-year college-going rates) and the predictor (e.g., student-to-counselor ratio), one could successfully expose the causal relationship between the predictor and the outcome. Unfortunately, the number of control variables that might fall into this category is inconceivably numerous, and many are simply unquantifiable. To completely eliminate bias, researchers need to rely on a source of randomness, which is hard to come by in the field of education.

There are, however, some examples in which this challenge is surmounted. Carrell and Hoekstra (2010) capitalized on the random placement of graduate student counselor interns and found that an additional counselor intern positively affected boys' reading and math achievement scores as well as reduced misbehavior in their sampled elementary schools. This type of randomness is analogous to a controlled experiment in which some schools are matched with an intern (treatment schools) and others are not (control schools), and it represents the "gold standard" through which causal inferences may be drawn. Such a scenario is not required, however, to make causal claims about the impacts of additional school counselors on student outcomes.

Also focusing on elementary schools, Reback (2010) examined the impact of an expanded counselor workforce within a school on that school's frequency of disciplinary infractions and on student achievement scores. Reback focused on Alabama, which, like several other states, mandates maximum student-to-counselor ratios. Reback's ability to draw causal inferences hinged on the likely assumption that schools with student enrollments just above a state-specified threshold are, on average, indistinguishable from those with student enrollments just below that threshold. Unlike Carrell and Hoekstra (2010), Reback did not find any substantial impact of additional counselors on achievement test scores in Alabama's elementary schools. In the present article, we modify Reback's regression discontinuity approach and present a stepwise guide for detecting the impact of school counselors on student outcomes, with 4-year college-going as the outcome of interest.

Method

Data Set and Sample

In this study, we use survey data from the NCES restricted-use SASS 1999–2000, 2003–2004, and 2007–2008 data files. The SASS is a repeated cross-sectional survey that collects information on teachers, principals, districts, and schools, with the intent of understanding school and teacher climates, pay structures, and general perceptions of these groups' professions. The SASS is particularly appealing in the context of this research because the survey collects from respondents the school's 4-year college-going rates, student enrollment, and number of counselors at the sampled schools, as well as school-level demographic characteristics such as minority representation and percentage of students eligible for free/reduced-price lunch. The Common Core of Data (CCD) is a complementary NCES data set that provides information on teacher full-time equivalency at the sampled high schools in SASS.

The design of this study (described below) necessitates the incorporation of data from states that have mandated maximum high school student-to-counselor ratios or have programs through which the states subsidize the hiring of counselors with school accreditation guidelines reinforcing these ratios. We selected states that have been identified by the American School Counselor Association or the National Association of State Boards of Education as recommending or mandating maximum student-to-counselor ratios at the high school level. We then contacted the state boards of education in these states for confirmation and historical information regarding these ratios and identified 12 states as

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specifying maximum student-to-counselor ratios. The states and specified ratios, along with whether we have confirmation that they were in place during the specified SASS year, are listed in Table 1.

From the SASS data, we found that the overall public high school student-to-counselor ratio has remained fairly constant over the past decade: 320:1 in 1999–2000, 331:1 in 2003–2004, and 319:1 in 2007–2008. However, across states, enormous variation exists in these ratios. For example, during the 2007–2008 academic year, the high school student-to-counselor ratios in Florida and Minnesota were approximately 400:1, whereas in the sampled state of Arkansas, this ratio approached 450:1. In the northeastern and New England states, these ratios were generally in the vicinity of 200:1 to 250:1. The percentage of graduating high school seniors immediately enrolling in a 4-year college also varies across the sampled states. When aggregated over all three waves of SASS, this estimate of immediate 4-year college enrollment was less than 30% in Utah and 50% or higher in the northern New England states.

Measures

We define each of the variables used in our empirical analyses and then present the empirical model that we estimate.

Student outcome. $FourYrCollege_{jt}$ is a continuous variable that measures the percentage of graduating high school seniors in School *j* and Year *t-1* who attended a 4-year college in Year *t*, where *t* represents one of the three SASS survey years.

Instrument. $Boundary_{jtk}$ is a collection of three dichotomous (0/1) variables representing each of the state's first three enrollment thresholds (beyond which data are sparse) where an additional counselor must be added to comply with the law. Each component is equal to 1 if High School *j*'s student enrollment in SASS Survey Year *t* is above that school's state-mandated enrollment threshold (*k*), and 0 otherwise. For example, in Oklahoma, where the mandated threshold is 450 students per high school counselor, the variable *Boundary1* = 1 at 451 students; *Boundary2* = 1 at 901 students, and *Boundary3* = 1 at 1,351 students.

TABLE 1

Public High School Student-to-Counselor Ratio Policies and Schools and Staffing Survey Academic Years During Which They Were Implemented

State and High School Maximum Student-to-Counselor Ratio	1999–2000	2003–2004	2007–2008
Alabama[a]			
1 counselor up to 499 students; 1.5 counselors up to 749 students; 2 counselors up to 999 students; 2.5 counselors up to 1,249 students; 3 counselors up to 1,499 students; 1 additional counselor for each additional 250 students	√	√	√
Arkansas[b]			
1 counselor per 450 students	√	√	√
Louisiana			
1 counselor per 450 students			√
Maine			
1 counselor per 250 students		√	√
Missouri[c]			
1 counselor per 301–375 (desirable); 500 minimum	√	√	√
Montana[d]			
1 counselor per 400 students	√	√	√
Nebraska[b]			
1 counselor per 450 students	√	√	√
New Hampshire			
1 counselor per 300 students	√	√	√
North Dakota[b]			
1 counselor per 450 students	√	√	√
Oklahoma			
1 counselor per 450 students	√	√	√
Utah			
1 counselor per 400 students	√	√	√
Vermont			
1 counselor per 300 students	√	√	√

Note. Policies were confirmed through the appropriate contacts at state departments of education where no legal documentation was easily acquired. In Nebraska, an additional half-time counselor must be added for each additional 225 students. This was not used as a threshold because such a cut point would result in double-counting of schools using a window size of ±125.
[a]In 1999–2000, the ratios in Alabama called for 0.5 counselors up to 499 students; 1 counselor up to 749 students; 2 counselors up to 999 students; 2.5 counselors up to 1,499 students; 1 additional counselor for each 250 students above 1,499. [b]Counselor ratio is mandated at the district level. [c]The desirable standards appear in the state accreditation guidelines and are the standards used in these analyses. The absolute minimum ratio is 500 students to 1 counselor. Missouri schools tend to adhere to the desired standards, and 375 is the cut point used in these analyses. [d]Montana Law 10.55.710, which specifies student-to-counselor ratios, was modified in 2000 and 2002. While we were unable to secure documentation to the unamended accreditation guidelines, a summary of amendments suggests that only "language," not policy, was updated.

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Endogenous predictor. $TotCounselor_{jt}$ is a continuous variable that equals the sum of full-time counselors and 0.5*part-time counselors in High School *j* during SASS Survey Year *t*.

Fixed effects. $Year_{jt}$ is a collection of two dichotomous variables indicating the SASS Survey Year *t* during which High School *j* was sampled; the omitted indicator is the 1999–2000 survey year. *$State_j$* is a collection of 11 dichotomous variables (with Maine as the omitted variable) indicating the state in which High School *j* exists.

Control predictors. $FreeLunch_{jt}$ is a continuous variable indicating the percentage of students approved for free or reduced-price lunch at High School *j* in SASS Survey Year *t*. *URM_{jt}* is a continuous variable indicating the percentage of underrepresented minority students at High School *j* in SASS Survey Year *t* who are Hispanic, Latino, African American, or Native American.

$FTETeach_t$. This is a continuous variable that equals the full-time equivalent (FTE) teachers from the CCD working in High School *j* during SASS Survey Year *t-1* when the focal students were seniors in high school.

$Enrollment_{jt}$. This is the student enrollment of High School *j* in SASS Survey Year *t*.

Method of Analysis

To draw causal inferences about the impact of high school counselors on 4-year college enrollment, we adopted a regression discontinuity design (RDD). This methodological approach is particularly well suited to address this article's research questions because the sample states have clear policies specifying that when student enrollment exceeds a specified threshold, an additional counselor must be hired. Undergirding this approach is the assumption that schools on either side of this state-mandated threshold are similar with respect to all observed and unobserved characteristics except the number of counselors employed.

The RDD approach was introduced by Thistlethwaite and Campbell (1960) as an alternative to relying on experimental research design to draw causal inferences. Researchers in the domain of education policy and practice are increasingly turning to this approach as a means of addressing a wide range of research questions, including the impact of financial aid on college student engagement (Boatman & Long, 2009), the impact of financial aid on college enrollment behavior (Van der Klaauw, 2002), and the effects of failing a high-stakes exit examination on high school graduation (Papay, Murnane, & Willett, 2010).

In general, data suitable for RDD require the implementation of either a *sharp* RDD or a *fuzzy* RDD. In the context of these analyses, if all sampled high schools adhered strictly to the state-mandated maximum student-to-counselor thresholds, a sharp RDD would be the preferred methodological approach. Under such a design, simply taking the difference between average outcomes immediately above and below the specified threshold would reveal the estimated impact of an additional counselor on our outcome variables (Lee & Lemieux, 2009).

Figure 1 shows the number of counselors (*y*-axis) plotted against high school enrollment by state, with vertical lines depicting the enrollment at which the number of counselors would be expected to jump based on state policy. Although a steplike pattern is clearly visible in Figure 1, schools clearly do not adhere strictly to the mandated ratios. This would not influence our analytic approach if compliance were unrelated to the outcome examined in this article (Angrist & Lavy, 1999). Intuition suggests that such an assumption is specious. Schools exceeding the mandated number of counselors may be located in areas with large tax bases and high-achieving students, or they may have many at-risk students and require a larger counselor staff to serve the students' needs. In the same vein, at least some noncompliance may be explained by the fact that a few of these school counselor mandates were fairly new edicts at the time of survey collection, and certain types of schools are quicker to adjust staffing to avoid punitive actions. To account for these confounding factors and to eliminate the endogeneity of the predictor variable, we adopted a fuzzy RDD, utilizing an instrumental variable approach, with the three boundary variables serving as instruments. We focus our analyses on conducting an instrumental variable approach through the commonly used method of two-stage least squares regression (2SLS).

The 2SLS approach used to estimate the impact of school counselors on 4-year college-going is straightforward and can be accommodated by most statistical software packages. In the first-stage equation (Equation 1) of our analyses, the estimated total number of counselors, *$TotCounselor_{jt}$* in High School *j* in SASS Year *t*, is regressed on three 0/1 indicator variables representing the first three state-specific maximum enrollment thresholds, *$Boundary_{jtk}$*, and the indicator variables *$Year_{jt}$*, *$State_t$*, as well as selected control variables listed above (Z_{jt}) and a function of continuous *$Enrollment_{jt}$*. In the second-stage equation (Equation 2), the outcome variable, *$FourYrCollege_{jt}$*, is regressed on the predicted values of *$TotCounselor_{jt}$* from Equation 1 while continuing to control for the covariates appearing in the first-stage equation (Murnane & Willett, 2011).

$$\begin{aligned} TotCounselor_{jt} = {} & \beta_0 + \beta_1 Boundary1_j + \beta_2 Boundary2_j + \\ & \beta_3 Boundary3_j + \lambda Year_{jt} + \\ & f(Enrollment_{jt}) + \phi State_j + \varphi Z_{jt} + \varepsilon_{jt} \end{aligned} \quad (1)$$

$$\begin{aligned} FourYrCollege_{jt} = {} & \alpha_0 + \chi Year_{jt} + \alpha_1 TotCounselor_{jt} + \\ & f(Enrollment_{jt}) + \tau State_j + \\ & \varphi Z_{jt} + \mu_{jt} \end{aligned} \quad (2)$$

The parameter, α_1, represents an unbiased estimate of an additional counselor on 4-year college-going rates in the same high school.

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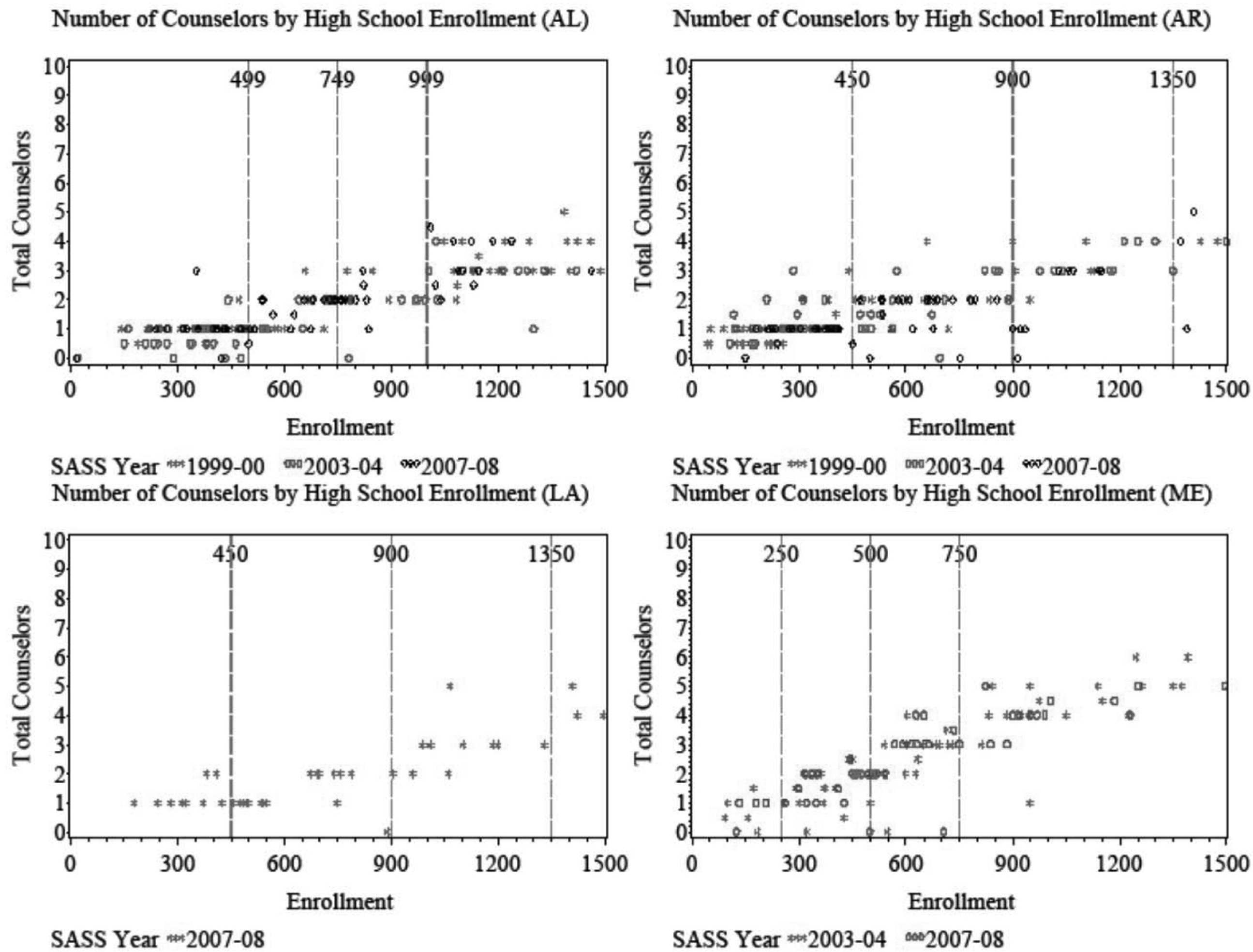

FIGURE 1

Relationship Between the Number of High School Counselors and High School Enrollment, by State

Note. AL = Alabama; AR = Arkansas; LA = Louisiana; ME = Maine; SASS = Schools and Staffing Survey.

Under the ideal scenario, our sample would be large enough to allow for a comparison of the 4-year college-going rates among schools with student enrollments at the enrollment threshold with schools with student enrollments exceeding the threshold by one student. This is an unrealistic expectation because we have data from a sample of all high schools in states with relatively few high schools. In fact, it is almost never the case in RDD that the data are so rich to allow for such a comparison. Therefore, we followed the established guidelines for modeling the relationship between the outcome (4-year college-going) and the forcing variable (student enrollment) among high schools not immediately flanking the enrollment boundaries. We modeled this relationship using the two techniques traditionally used in RDD studies: polynomial regression and linear regression over a restricted range of data in the locale of the enrollment boundaries. With the former method, we modeled the relationship between 4-year college-going and student enrollment over the entire sample using a fourth-order polynomial expression for enrollment (i.e., enrollment, enrollment squared, enrollment cubed, quartic enrollment). With the latter, we restricted the sample to only those schools with student enrollments ±125 students from the nearest threshold boundary (Hahn, Todd, & Van der Klaauw, 2001; Lee & Lemiuex, 2009; Lee, Moretti, & Butler, 2004). Both methods yielded the same estimates of the causal impact of an additional counselor on 4-year college-going rates, which was reassuring.

Results

Before discussing the impact estimates, we first present the results of the first-stage model (Equation 1) in Table 2, which conveys several important points. First, across each of the three enrollment thresholds, the predicted number

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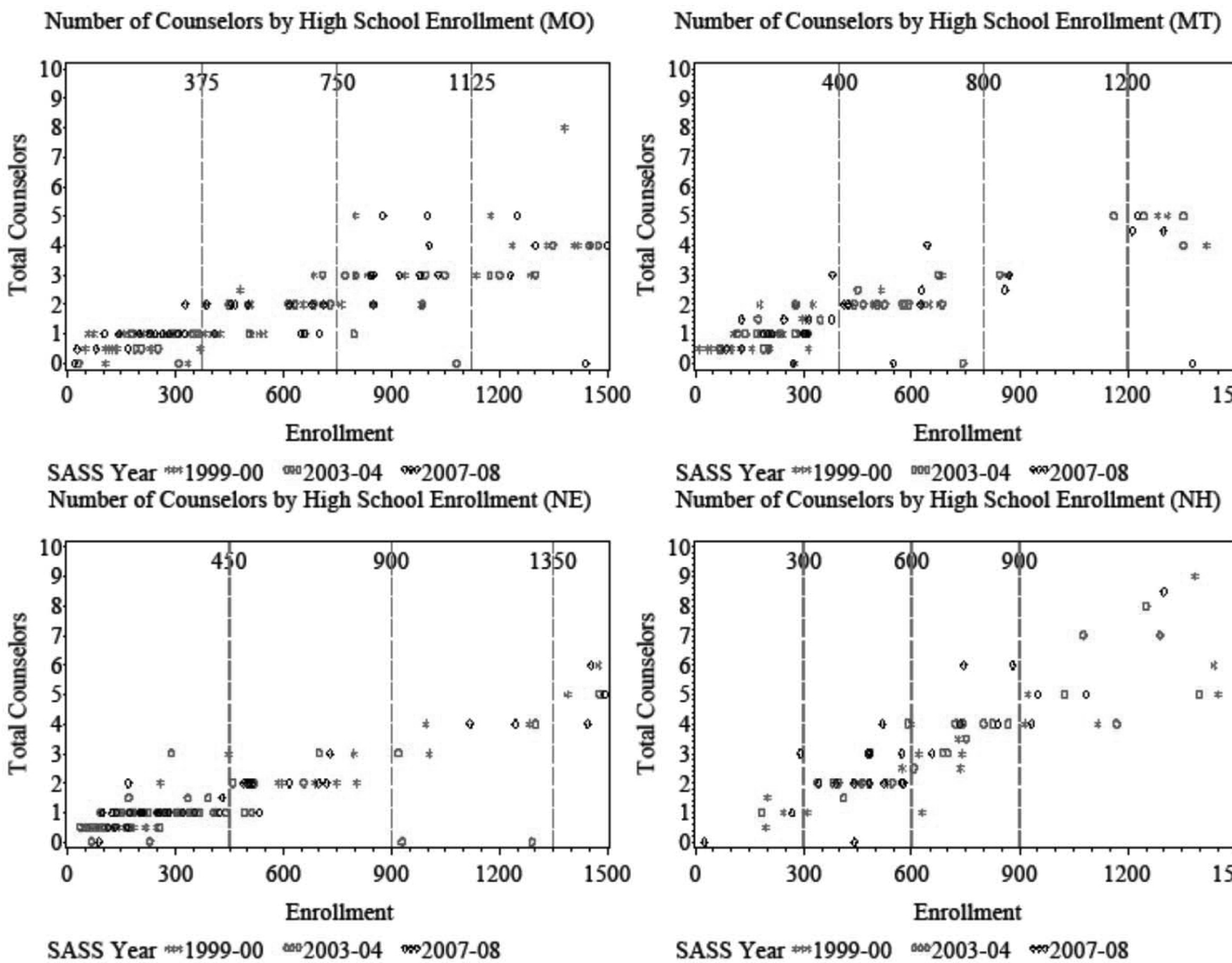

FIGURE 1 (*Continued*)

Relationship Between the Number of High School Counselors and High School Enrollment, by State

Note. MO = Missouri; MT = Montana; NE = Nebraska; NH = New Hampshire; SASS = Schools and Staffing Survey.

of school counselors increased, even after controlling for the forcing variable of high school enrollment. With the exception of the parameter estimate associated with the *Boundary1* variable in Specification 3, all regression coefficients associated with the boundary variables demonstrated statistical significance. The jumps in the predicted number of counselors appeared to be largest for the *Boundary3* variable. With a parameter estimate of 0.49 (p = .002), the expected jump in the total number of counselors around the third enrollment threshold in Specification 3 of Table 2 was equivalent to the addition of one half-time counselor. Around the second enrollment threshold (Specification 3), which would be 900 students in states with mandates of 450 students per counselor, the jump in the expected number of counselors was approximately 0.40 (p = .001).

The next finding of interest in Table 2 is that the percentage of students approved for free/reduced-price lunch was not associated with an increase in school counselor staffing. Similarly, the gender composition of the high school was unrelated to the total number of high school counselors. The percentage of students who belonged to an underrepresented minority group was positively associated with counselor staffing and, while these point estimates were statistically significant, the magnitude of these parameter estimates were less than 0.01 (Specifications 2 and 4). Collectively, the variables presented in Table 2 accounted for 60% to 70% of the total variation in counselor staffing counts, as indicated by the R^2 values.

Table 3 shows the impact of an additional high school counselor on the percentage of graduating seniors who attended a 4-year college in the year following their graduation from high school. We present the impact estimates using both

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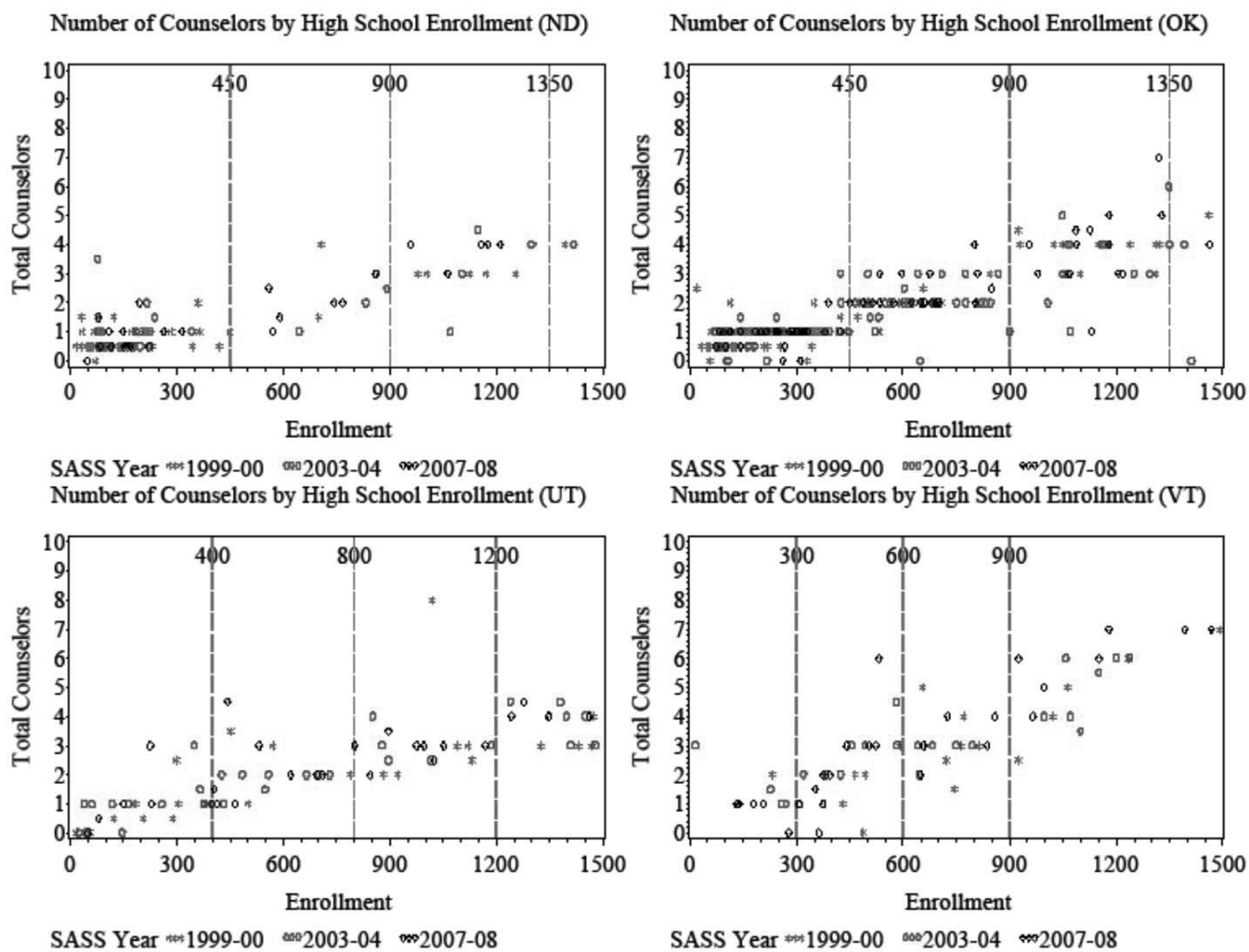

FIGURE 1 (*Continued*)

Relationship Between the Number of High School Counselors and High School Enrollment, by State

Note. ND = North Dakota; OK = Oklahoma; UT = Utah; VT = Vermont; SASS = Schools and Staffing Survey.

correlational and causal frameworks, and through parametric polynomial and local linear regression. Specifications 1, 2, 5, and 6 show the ordinary least squares (OLS) regression results. Although this analytic technique reveals the relationship between the counselor staffing and 4-year college-going after accounting for the relevant covariate values, it is not a causal framework. The OLS technique used for these four specifications is equivalent to the second stage of the 2SLS technique discussed earlier, except the actual number of counselors is used as a covariate rather than the predicted value from Equation 1.

OLS estimates are strikingly similar in Specifications 1, 2, 5, and 6. In Specification 6, after accounting for a host of relevant covariates, the noncausal relationship suggests that an additional high school counselor was associated with a 2.49 percentage point (p = .004) increase in 4-year college-going rates. The causal estimates in Table 3 are larger in magnitude than the OLS estimates, suggesting that the OLS estimates of the impact of an additional school counselor on 4-year college-going rates understate the true causal impact of an additional counselor. For example, in Specification 7 in Table 3, we show than an additional counselor caused a 9.91 percentage point (p = .033) increase in 4-year college-going rates. As with the OLS estimates, the 2SLS estimates are of a similar magnitude across specifications.

Although the magnitude of the causal counselor impact estimates are larger than those accompanying the OLS analyses, the standard errors of the causal estimates are also larger. Therefore, beyond stating that additional counselors do exert a causal impact on the 4-year college-going rates,

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TABLE 2

Estimated Increase in Counselor Staffing Across Discontinuity Boundaries

	Window of ± 125 Students				Full Sample			
	Specification 1		Specification 2		Specification 3		Specification 4	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Boundary 1	0.18*	0.09	0.24***	0.09	0.07	0.09	0.18**	0.09
Boundary 2	0.29**	0.14	0.30**	0.13	0.40***	0.12	0.41***	0.12
Boundary 3	0.41**	0.17	0.33*	0.18	0.49***	0.16	0.34**	0.16
Enrollment/100	0.23***	0.03	0.09**	0.04	0.14	0.11	0.16	0.11
% URM			0.00**	0.00			0.00***	0.00
% free/reduced lunch			0.00	0.00			0.00	0.00
% male			0.00	0.01			0.00	0.00
Full-time equivalent teachers			0.02***	0.00			0.02***	0.00
Enrollment^2/10,000					0.03	0.04	–0.01	0.04
Enrollment^3/1,000,000					0.00	0.00	0.00	0.00
Enrollment^4/100,000,000					0.00	0.00	0.00	0.00
Observations	671		609		1,335		1,236	
R^2	0.60		0.64		0.67		0.70	
Concentration parameter	9.48		10.38		19.35		16.80	

Note. Fixed effects for Alabama, Arkansas, Louisiana, Missouri, Montana, Nebraska, New Hampshire, North Dakota, Oklahoma, Utah, Vermont, and year of Schools and Staffing Survey (SASS) administration included in all models. Enrollment thresholds are 450, 900, and 1,350 for Arkansas, Louisiana, Nebraska, North Dakota, and Oklahoma; 400 for Montana and Utah; 300, 600, and 900 for New Hampshire and Vermont; 375, 750, and 1,125 for Missouri; 499, 749, and 999 for Alabama; 250, 500, and 750 for Maine. Full-time equivalent teacher counts come from Common Core of Data 1998–1999, 2002–2003, and 2006–2007. All other variables come from SASS. Full sample includes all schools with student enrollments less than or equal to the state's third enrollment threshold plus 125. The concentration parameter equals the number of instruments (in this case, 3) multiplied by the *F* statistic associated with the hypothesis that Boundary 1 = Boundary 2 = Boundary 3 = 0. The metric is used to relay the strength of the first-stage equation when there exist multiple instruments. *SE* = robust standard error; URM = underrepresented minority (Hispanic/Latino, African American, or Native American).
**p* < .10. ***p* < .05. ****p* < .01.

we feel less comfortable accepting these fairly large point estimates as gospel. That said, the causal counselor impact estimates are not outside of the realm of possibility. Among the typical sampled high school with an enrollment of about 113 students, our results imply that an additional high school counselor would be predicted to induce 11 more graduating students into 4-year colleges. Some of these students might be shifted from the workforce into the 4-year college pipeline, and others might be shifted from the 2-year college pipeline into the 4-year college pipeline. Moreover, there will obviously be diminishing returns to adding more counselors to the school. Although the biggest jump in 4-year college-going might be achieved from increasing the number of school counselors from one to two, it is unlikely that a comparably large jump would be achieved by increasing the number of school counselors from three to four. Unfortunately, because of sample size constraints, we were unable to analyze the impacts of additional school counselors with such granularity. However, large state-level administrative data sets may permit this type of analysis in the future.

In summary, we found that an additional high school counselor might increase a high school's 4-year college-going rate by about 10 percentage points. Among the sampled high schools, the mean 4-year college-going rate was 42.3%, with a standard deviation of approximately 21.9%. To contextualize the effect size of our results, it is useful to think about our main finding in terms of standard deviation units. An additional counselor would be expected to increase a high school's 4-year college-going rate by about 0.5 standard deviation units—an effect size that is far from trivial.

Sensitivity Analyses

A potential threat to the validity of this study's conclusions is the 1-year lag between reported 4-year college-going rates and the total number of high school counselors. The SASS school survey respondent, generally the principal, was asked for the 4-year college-going rates in Year *t-1* (e.g., 2006–2007) and the total number of counselors employed in Year *t* (e.g., 2007–2008). Most certainly, some of the sampled schools increased or decreased the number of counselors between Year *t* and Year *t-1*, although we are unable to identify these schools and the accompanying changes in counselor counts. Similarly, student enrollments differ between Year *t* and Year *t-1*, and this means that the expected number of counselors based on student enrollment for a particular school may differ between these 2 years.

It is challenging to predict the direction or magnitude of bias resulting from these annual shifts. It is likely that many, but not all, changes in counselor numbers at a given school are a direct result of changes in student enrollment. If fluctuations in school enrollment and the resulting changes in

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TABLE 3

Impact of an Additional School Counselor on 4-Year College-Going Rates

	Window of ± 125 Students								Full Sample							
	Correlational OLS				Causal 2SLS				Correlational OLS				Causal 2SLS			
	Spec. 1		Spec. 2		Spec. 3		Spec. 4		Spec. 5		Spec. 6		Spec. 7		Spec. 8	
Variable	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***	**Est.**	***SE***
Counselors	2.97***	0.95	2.66***	0.99	14.43***	7.19	12.80*	7.66	2.46***	0.82	2.49***	0.87	9.91**	4.63	12.95**	6.07
Enrollment/100	0.09	0.36	–1.41**	0.56	–3.41	2.22	–3.12**	1.40	6.89**	2.99	2.66	3.27	6.13**	3.10	1.86	3.43
% URM			0.02	0.05			–0.02	0.05			–0.08**	0.03			–0.11***	0.04
% free/ reduced lunch			–0.09*	0.05			–0.09*	0.05			–0.05	0.03			–0.04	0.04
% male			–0.12	0.11			–0.17	0.13			–0.09	0.09			–0.14	0.09
Full-time equivalent teachers			0.26***	0.08			0.03	0.19			0.31***	0.08			0.10	0.15
Enrollment^2/ 10,000									–1.98**	0.83	–1.39	0.89	–2.24**	0.88	–1.50	0.94
Enrollment^3/ 1,000,000									0.21**	0.09	0.16*	0.09	0.23**	0.09	0.16	0.10
Enrollment^4/ 100,000,000									–0.01**	0.00	–0.01*	0.00	–0.01**	0.00	–0.01	0.00
Observations	671		609		671		609		1,335		1,236		1,335		1,236	
R^2	0.23		0.25		0.04		0.12		0.21		0.22		0.15		0.12	

Note. Fixed effects for Alabama, Arkansas, Louisiana, Missouri, Montana, Nebraska, New Hampshire, North Dakota, Oklahoma, Utah, Vermont, and year of School and Staffing Survey (SASS) administration included in all models. Enrollment thresholds are 450, 900, and 1,350 for Arkansas, Louisiana, Nebraska, North Dakota, and Oklahoma; 400 for Montana and Utah; 300, 600, and 900 for New Hampshire and Vermont; 375, 750, and 1,125 for Missouri; 499, 749, and 999 for Alabama; 250, 500, and 750 for Maine. Full-time equivalent teacher counts come from Common Core of Data 1998–1999, 2002–2003, and 2006–2007. All other variables come from SASS. Full sample includes all schools with student enrollments less than or equal to the state's third enrollment threshold plus 125. OLS = ordinary least squares; 2SLS = two-stage least squares regression; Spec. = specification; Est. = estimate; *SE* = robust standard error; URM = underrepresented minority (Hispanic/Latino, African American, or Native American).
*$p < .10$. **$p < .05$. ***$p < .01$.

counselor counts are generally random and unrelated to this study's outcomes, then the 2SLS estimates presented in this article remain unbiased. In light of the anticipated and evident positive relationships between our outcome variables and the total number of counselors, schools sliding to the right of the threshold from Year *t-1* to Year *t* would be expected to have increased the number of counselors between these 2 years, and the 4-year college-going rates in Year *t* would be expected to increase relative to Year *t-1*. The converse would occur among schools sliding to the left of the nearest enrollment threshold. Put simply, we suspect that, on average, schools just to the right of the threshold may boast higher college-going rates in Year *t* compared with Year *t-1*, whereas schools just to the left of the threshold will experience lower college-going rates in Year *t* compared with Year *t-1*. Therefore, if any estimate bias is generated from timing issues, it is likely a downward bias, which translates into an understatement of the true impact of counselors on student-level outcomes. Of course, annual shifts in counselor staffing occur slowly. Undulations in student enrollment causing schools to weave back and forth across a threshold would generally not result in annual firing and rehiring of counselors. Not only does this phenomenon provide a plausible explanation for the discontinuity fuzziness, it also allays our concerns regarding the lag between outcomes and counselor staffing counts.

That said, we have the capacity to address this threat to validity beyond simply rationalizing our choices. Ideally, we would have access to the number of counselors and student enrollment at each of the sampled schools during Year *t-1*. Because SASS is not longitudinal and is administered every 4 years, this is not possible. Fortunately, we can tackle this issue with NCES's CCD. As a first sensitivity check, we isolated only the schools with the same expected number of counselors in Years *t* and *t-1* based on student enrollment during these 2 years from the CCD and SASS. Using this subsample, we then refitted Equations 1 and 2. With this restriction, our sample size decreased by about 15% in the full sample, more than half of which was a direct result of missing CCD data rather than crossing over enrollment thresholds per se. Using polynomial regression on this restricted sample, we found that the estimate in Specification 7 of Table 3 held steady at about 12 percentage points ($p = .040$).

As a second sensitivity check, we addressed the possible differences in counselor staffing at a school between Year *t* and Year *t-1*. Unlike enrollment, the CCD does not contain any data on the number of counselors at the school level. However, these data are available at the district level. We isolated the schools with the smallest changes (less than 0.5 school counselors) in secondary school counselors in

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the district between t and t-1. Many schools excluded from this category likely did not experience shifts in counselor staffing, but the included schools are least likely to have experienced such shifts. Under this specification, we continued to find a statistically significant relationship between an additional counselor and 4-year college-going rates, with an estimated impact of 13.8 percentage points (p = .003).

Discussion

How Additional Counselors Might Improve Student Outcomes

In this study, we find strong evidence that an additional high school counselor favorably affects 4-year college-going rates. However, as previously noted, the data in this study do not shed light on the mechanism behind this result. In contrast to teacher labor force expansion, which is generally perceived to improve student outcomes through class size reduction, the mechanism of impact by which additional counselors contribute to such improvements is less clear. It is certainly plausible that the staffing ratio argument emphasized in teacher impact studies is applicable to counselors as well. The addition of counselors to a high school should free up time for counselors to work with more students or for counselors to allocate more time for students. If the student demand for counselors is already met, an additional counselor can generate more demand by proactively targeting students who might not otherwise have thought about college.

Alternatively, more counselors in a school translates into greater opportunities for a student to match with a counselor who can ably address that student's specific needs. As discussed in the introduction, counselors wear many hats and are expected to nimbly resolve a variety of issues. If the additional counselor's skill set is a perfect replica of one already existing among the counseling staff, then he or she can only improve student outcomes through the student-to-counselor ratio reduction mechanism. Of course, the probability is close to zero that two persons' skill sets are identical, even if they received identical training. Therefore, it is quite likely that an increased breadth and depth of counseling skills resulting from additional staff is at least partially responsible for a jump in positive student outcomes.

Assessing Whether Counselors Are a Cost-Effective Investment

The association between educational attainment and future labor market outcomes is well documented. Baum, Ma, and Payea (2010) estimated that, on average, individuals whose highest education attainment is a bachelor's degree earn 66% more than individuals with only a high school degree and 134% more than individuals without a high school degree over the course of a lifetime. Too much uncertainty exists around the causal impact of educational attainment on future earnings to quantify how an additional counselor might influence lifetime earnings and the tax revenues generated from these increased earnings. That said, it is certainly within the realm of possibility that increases in tax revenues directly resulting from an additional counselor would well exceed the costs of hiring that additional counselor.

Experimental evidence from the Tennessee Student Teacher Achievement Ratio (STAR) experiment (Dynarski, Hyman, & Schanzenbach, 2011) does allow for a comparison between the impacts on college-going of reducing class size in elementary grades and expanding the high school counseling staff. In the Tennessee STAR experiment, students were randomly assigned to smaller (13 to 17 students) or larger (22 to 25 students) classrooms in Grades K–3. Students in the treatment group were no more likely to have attended a private or public 4-year college by age 30 compared with those in the control group, despite the modest 2.5 percentage point increase in first-time 2-year college attendance among students from the Tennessee STAR treatment group (Dynarski et al., 2011). With respect to increasing 4-year college-going rates, investing in additional school counselors is clearly superior to class size reduction in elementary grades.

Recent research has suggested that dismantling some of the financial aid application barriers to college also increases college enrollment rates. Working closely with H&R Block tax professionals, Bettinger, Long, Oreopoulos, and Sanbonmatsu (2012) showed that dependent students who were offered assistance with completion and submission of the Free Application for Federal Student Aid, as well as the estimated costs of attending local 2- and 4-year colleges, were 8 percentage points more likely to attend college within 1 year of treatment exposure. This effect encompasses enrollment in both 2- and 4-year colleges, unlike the estimates in this article, which addresses 4-year college enrollment only.

Conclusion

With this study, we offer evidence that high school counselors positively influence 4-year college-going rates for their students. The 2SLS estimates are somewhat large, and although it is tempting to hone in on these point estimates and accept their magnitude unwaveringly, we caution against such inclinations. Through our analyses, we have captured a statistically significant impact of an additional counselor, but the standard errors associated with our estimates are large. For example, in Specification 7 of Table 3, the 90% confidence interval of the causal impact of an addition high school counselor on 4-year college-going rates spans 2.3 to 17.5 percentage points.

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The natural progression of empirical teacher impact studies is a model that should serve as a template for high school counselor impact studies. Ours is the first study broaching this topic, and we hope and anticipate that it will not be the last. Perhaps most importantly, we provide a foundation for states to track the progress of student outcomes with the addition of high school counselors. Variation in high-school-level counselor counts over time that results from exogenous state-level policies is ideally suited for developing a clear and more precise understanding of counselors' true impact on student outcomes. A narrowing of plausible estimates in this article and an examination of the differential impacts by student race, socioeconomic status, and gender mean that policymakers and school administrators will have a clearer understanding of whether or not augmented counselor staffing is prudent and financially advisable given the school's broader goals.

This research has powerful implications in terms of affirming the perception that counselors are unable to allocate an adequate amount of time toward developing college-going cultures at their high schools. Results from the College Board's 2012 National Survey of School Counselors and Administrators revealed that more than half of high school counselors believe that school counselors should spend "a little more" or "a lot more" time on building a college-going culture (Hart Research Associates, 2012). If these sentiments represented the reality of the school counseling landscape, one might expect that additional counselor staffing would free up time for counselors to more effectively shape their high schools' college-going cultures. Our findings suggest not only that counselors' perceptions are correct but also that increases in counselor staffing achieve powerful results in bolstering college attendance. This evidence can be leveraged by counselors and administrators alike to defend claims that current counselor staffing levels are suboptimal and that students are being penalized as a result.

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