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# A Proposal for Causal Analysis of School-Level Resources: The Effect of Counselor Caseload Size on College Enrollment

## Context

This paper aims to contribute to the field of educational research by developing a causal method that can measure variation in the type and quantity of resource allocation (Sorenson & Hallinan, 1977; Sorenson & Morgan, 2000). I demonstrate this method by testing the effects of the allocation of high school counselors' caseload sizes on college enrollment in public schools on college enrollment.

## Research Question

In addition to determining whether caseload size affects *all* students, this paper further seeks to explore the heterogeneity of the treatment effect, a hypothesis supported by qualitative literature (Bryan, Moore-Thomas, Day-Vines, & Holcomb-McCoy, 2010; Erickson, 1975; Farmer-Hinton & Adams, 2006; Stanton-Salazar, 1995). Two research questions guide this study: (1) what is the effect of counselors' caseload size on students' college enrollment? (2) Does this treatment effect vary between students, based on their likelihood of attending college?

## Setting

This analysis uses survey data from individuals, schools, and districts. Thus, there is particular location in which the research was conducted.

## Subjects

The sample generated from the combined dataset is a nationally representative of public high school students, schools, and districts from the High School Longitudinal Study (HSLS). The first four waves were collected in between 2009 and 2016, with students who were 9th graders in 2009.

## Intervention

The intervention, or the causal variable, is a dichotomized indicator for "low caseload," which is equal to counselor caseloads of 250 students or fewer per the recommendations of American School Counselor's Association (ASCA, 2015). The outcome variable is a dichotomous measure of whether students are either enrolled in a four-year college in the fall of 2013, the fall after their senior year.

## Research Design

The first source of selection includes confounders such as residential segregation, choice, and mobility, which contribute to a form of non-voluntary selection. (McDermott, Frankenberg, & Diem, 2015). The second source of selection is the heterogeneous effects of treatment, itself. To address these sources of selection, I employ a weighted regression model. The first source of selection is addressed by constructing average treatment on the treated (ATT) weights using the predicted probability of being selected into the treatment group, $\hat{p}$ (Morgan & Winship, 2015).[1] Equation 1a and 1b demonstrates that the likelihood of selection into the treatment group for those already in the treatment group and for those in the control group.

$$For\ d_i = 1: w_{i,ATT} = 1 \tag{1a}$$

$$For\ d_i = 0: w_{i,ATT} = \frac{\hat{p}}{1-\hat{p}_i} \tag{1b}$$

To address the issue of treatment effect heterogeneity, I analyze the effect size within and between propensity score strata, which are constructed using the likelihood of attending college given their background and school and district context. The sample is divided into six strata based on propensity scores, which are defined such that the treatment and control group means within each stratum have a p-value less than 0.01 (DellaPosta, 2013). Thus, the treatment and control groups within each stratum are imperfectly balanced, just as they are in the complete sample for the weighted regression. Because I am unable to adjust for all sources of non-voluntary selection as well as the recursive relationship between the school's overall college-going rate, which is unobserved, and the counselor's goal prescience and prioritization of college in their time, I limit analysis to measurement of the ATT, as demonstrated in Figure 1.

**Data Collection and Analysis**

I match HSLS data with the Common Core of Data (CCD) and the American Community Survey (ACS). This study uses listwise deletion to address missing data issues. While multiple imputation (Rubin, 1977) is considered a rigorous form of addressing missing data (Allison, 2000), it does not allow for the estimation of propensity scores, critical to the analytic strategy of this paper.

**Results**

Weighted regression estimates in Table 3 suggest that students who are in schools in which counselors have caseloads with fewer than 250 students are five percent more likely to attend college than students in the control group. This effect is consistent regardless of specification. This result is half of the results from the conditioned multivariate regression in

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[1] A goal of weighted regression is balancing the means of the treatment and control groups, thereby seeking to meet the conditions of partial ignorability. As such, engaging in datamining to determine a propensity score and subsequent weight, which balances the treatment and control group is permissible (Morgan & Winship, 2015). Variables used to develop the datamined weight to balance the treatment and control group include the primary covariates and squared terms for SES, percent free-and-reduced lunch, racial composition of the school, percent of district that is poor and has a bachelors' degree, GPA. Other variables include an interaction between a student's race and whether they intend to complete the FAFSA, whether the school offers financial aid counseling, parental expectations of college, the extent to which students speak with their parents about financial aid, a student survey question of whether student fails to study because they can't afford college, and whether the family can afford college.

Table 2. Strata-specific results in Table 6 confirm that caseload size effect is, in fact, heterogeneous. The effect of treatment is larger for students who are less likely to attend college than it is for students who are more likely to attend college. This trend is especially pronounced as covariates are included. The effects of caseload size for students in strata 3 and 4 are between 0% and 2%, compared to between 5% and 7% for students in strata 1 and 2, which are the strata of students least likely to attend college based on prior characteristics.

**Conclusion**

The limitations of this study are varied. First, the mechanisms of influence between caseload size and college-going may include the unequal allocation of human capital between schools as demonstrated by Table 7. Thus, caseload size may simply be serving as a proxy for the many ways in which capital is distributed between schools. Rather, than negation of findings, these findings implore researchers to consider the influence of a variety of resource allocation mechanisms on college-going. Despite some tradeoffs resulting from small cell sizes and complexity of resource allocation, this method of analysis demonstrates the potential for measuring the causal effects of school resources in a more nuanced manner that allows for causal inference.

## Appendix A: Figures and Tables

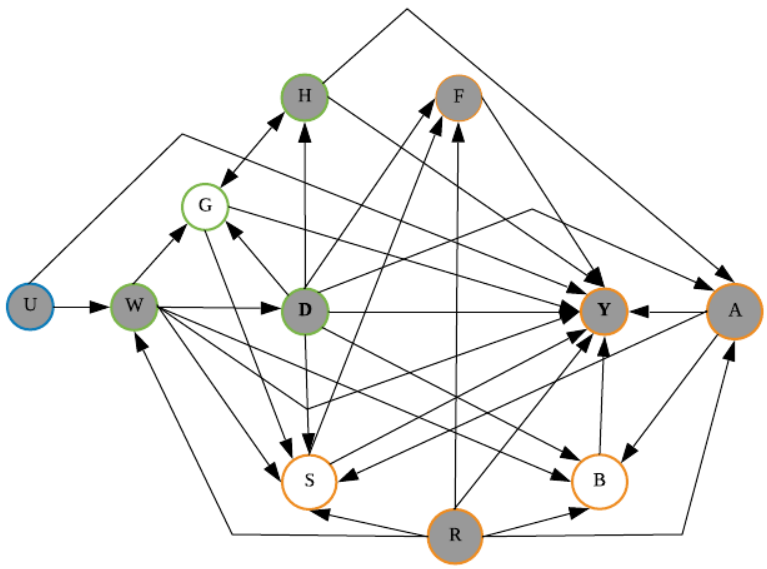


*Figure 1: Directed Acyclic Graph of Causal Effect of Caseload Size on College-Going*

**Table 1**: Descriptions, means, and standard deviations of outcome variable and pre-treatment covariates by treatment group, weighted by analytic weights

| | $D_i$=1 | | $D_i$=0 | |
|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD |
| Outcome: College-going (12th) | 0.65 | 0.48 | 0.55 | 0.50 |
| Student: Parent attended college | 0.30 | 0.46 | 0.34 | 0.47 |
| Student: Underrepresented race | 0.35 | 0.48 | 0.42 | 0.49 |
| Student: Socioeconomic status | -0.12 | 0.69 | -0.12 | 0.74 |
| School: Percent FRL | 0.47 | 0.23 | 0.43 | 0.21 |
| School: Percent of White / Asian in school | 0.64 | 0.33 | 0.59 | 0.29 |
| District: Urban area* | 0.23 | 0.42 | 0.29 | 0.45 |
| District: Percent poor* | 0.15 | 0.08 | 0.16 | 0.07 |
| District: Percent with bachelor's degree* | 0.26 | 0.12 | 0.26 | 0.07 |

N = 10,950 (9,698 in treatment and 1,325 in control), HSLS provided weights are used

Unless otherwise noted, all student- and school-level variables are drawn from 9th grade student data, collected in 2009

*Variables are drawn from the American Community Survey's 2011-2015 five-year estimates. We extrapolate that the values are indicative of area statistics for the relevant years of students' 12th grade year, which is 2013. All other variables are derived from the HSLS 2009-2013 survey.

**Table 2**: Logistic Regression Estimates

| Method | Treatment Effect |
|---|---|
| Logit regression estimation | |
| Naïve estimate* | 0.43 (0.10) |
| Predicted probability when T=0 | 0.55 (0.01) |
| Predicted probability when T=1 | 0.65 (0.02) |
| Multiple regression* | 0.52 (0.12) |
| Predicted probability when T=0 | 0.55 (0.01) |
| Predicted probability when T=1 | 0.66 (0.02) |

n = 11,023

**Table 3:** Weighted Logistic Regression Estimates of the ATT

| | Coefficient (SE) |
|---|---|
| Method | ATT weight |
| Model 1: Weighted regression* | |
| Estimate | 0.22 (0.11) |
| Treatment = 0 | 0.60 (0.01) |
| Treatment = 1 | 0.65 (0.02) |
| Model 2: Weighted regression & doubly robust* | |
| Estimate | 0.26 (0.12) |
| Treatment = 0 | 0.60 (0.01) |
| Treatment = 1 | 0.65 (0.02) |
| Model 3: Common support°^ | |
| Estimate | 0.22 (0.11) |
| Treatment = 0 | 0.60 (0.01) |
| Treatment = 1 | 0.65 (0.02) |
| Model 4: Common support & doubly robust^ | |
| Estimate | 0.26 (0.12) |
| Treatment = 0 | 0.60 (0.01) |
| Treatment = 1 | 0.65 (0.02) |

*n=7,203 for Di = 1 and n=10,545 for Di=0

^n = 7,188 for Di=1 and n = 10.532 for Di=0

° 38 cases fell below the lower bound of (~0.008) and 0 cases fell above the upper bound of (~0.722) the predicted probability of treatment $(\hat{p})$ and are, therefore, dropped

*Note:* Model 1 regresses college-going on caseload size. Model 2 repeats this regression but also includes the covariates from the conditioning set used earlier. The estimates do not vary significantly. While the log odds increase from 0.22 to 0.26, the predicted probabilities remain the same. Thus, a doubly robust estimate does little to change the effect of treatment. In models 3 and 4, the sample is limited to common support. In sum, 38 cases are dropped as they fall outside of the lower and upper bounds of the propensity score, $\hat{p}$. This confirms the overlap between the original treatment and control groups discussed earlier. Furthermore, model 4, which uses a doubly robust estimator just as model 2 did yields similar estimates to model 2. The ATT weight in this regression is constructed from a datamined weight from Equation 1a and 1b.

**Table 4**: Number of treated and control cases in each propensity score stratum

| Propensity score strata | P ($D_i = 1$) | Treated cases | Control cases |
|---|---|---|---|
| Stratum 1 | [0 – 0.11) | 263 | 3675 |
| Stratum 2 | [0.11 – 0.13) | 149 | 1459 |
| Stratum 3 | [0.13 – 0.21) | 840 | 5427 |
| Stratum 4 | [0.21 – 0.61) | 658 | 3280 |

*Note: Propensity scores are divided into strata based on mean differences with p-values of <0.001 between treatment and control groups.*

**Table 5:** Mean Distribution of Outcome Variable and Covariates over Strata

| | Stratum 1 [0 – 0.11) | | Stratum 2 [0.11 – 0.13) | | Stratum 3 [0.13 – 0.21) | | Stratum 4 [0.21 – 0.61) | |
|---|---|---|---|---|---|---|---|---|
| | $D_i = 1$ | $D_i = 0$ | $D_i = 1$ | $D_i = 0$ | $D_i = 1$ | $D_i = 0$ | $D_i = 1$ | $D_i = 0$ |
| College-going | 0.33 | 0.44 | 0.51 | 0.45 | 0.50 | 0.46 | 0.48 | 0.43 |
| Parent attended college | 0.55 | 0.58 | 0.46 | 0.52 | 0.45 | 0.44 | 0.29 | 0.28 |
| Underrep race | 0.76 | 0.49 | 0.56 | 0.41 | 0.31 | 0.27 | 0.26 | 0.20 |
| SES | -0.48 | -0.10 | -0.20 | -0.12 | -0.03 | -0.06 | -0.12 | -0.07 |
| Pct FRL | 0.47 | 0.36 | 0.41 | 0.38 | 0.39 | 0.40 | 0.51 | 0.53 |
| Pct White & Asian | 0.36 | 0.53 | 0.58 | 0.65 | 0.72 | 0.72 | 0.72 | 0.73 |
| Urban area* | 0.25 | 0.33 | 0.19 | 0.21 | 0.12 | 0.18 | 0.09 | 0.17 |
| Pct poor* | 0.22 | 0.18 | 0.16 | 0.15 | 0.14 | 0.14 | 0.13 | 0.15 |
| Pct with bach degree* | 0.24 | 0.25 | 0.27 | 0.26 | 0.26 | 0.26 | 0.24 | 0.25 |

**Table 6**: Weighted Logistic Estimates of the ATT over Strata

| Method | Stratum 1 | Stratum 2 | Stratum 3 | Stratum 4 |
|---|---|---|---|---|
| Model 1: Logistic regression* | | | | |
| Estimate | 0.20 (0.39) | 0.19 (0.34) | 0.07 (0.17) | 0.29 (0.15) |
| Treatment = 0 | 0.54 (0.05) | 0.58 (0.03) | 0.65 (0.02) | 0.56 (0.02) |
| Treatment = 1 | 0.59 (0.08) | 0.72 (0.07) | 0.67 (0.03) | 0.63 (0.03) |
| Model 2: Doubly robust logistic regression* | | | | |
| Estimate | 0.32 (0.38) | 0.39 (0.33) | -0.01 (0.15) | 0.10 (0.16) |
| Treatment = 0 | 0.53 (0.03) | 0.66 (0.03) | 0.67 (0.02) | 0.59 (0.02) |
| Treatment = 1 | 0.59 (0.07) | 0.73 (0.05) | 0.66 (0.03) | 0.61 (0.03) |
| Model 3: Common support°^ | | | | |
| Estimate | 0.21 (0.41) | 0.19 (0.35) | 0.07 (0.17) | 0.29 (0.15) |
| Treatment = 0 | 0.54 (0.05) | 0.68 (0.03) | 0.65 (0.02) | 0.56 (0.02) |
| Treatment = 1 | 0.59 (0.09) | 0.72 (0.07) | 0.67 (0.03) | 0.63 (0.03) |
| Model 4: Common support & doubly robust°^ | | | | |
| Estimate | 0.25 (0.38) | 0.39 (0.33) | -0.01 (0.15) | 0.10 (0.16) |
| Treatment = 0 | 0.54 (0.03) | 0.66 (0.03) | 0.67 (0.02) | 0.59 (0.02) |
| Treatment = 1 | 0.59 (0.08) | 0.73 (0.05) | 0.67 (0.03) | 0.61 (0.03) |

*Sample counts per strata: $n_{stratum1} = 2{,}614$; $n_{stratum2} = 1{,}115$; $n_{stratum3} = 4{,}415$; $n_{stratum4} = 2{,}879$
^Sample counts per strata: $n_{stratum1} = 1{,}645$; $n_{stratum2} = 700$; $n_{stratum3} = 2{,}932$; $n_{stratum4} = 1{,}911$

**Table 7:** Descriptions, means, and standard deviations of school-level characteristics by treatment group, weighted by analytic weights

| Variable | $D_i$=1 Mean | $D_i$=1 SD | $D_i$=0 Mean | $D_i$=0 SD |
|---|---|---|---|---|
| Years of principal experience | 7.24 | 5.42 | 6.93 | 5.70 |
| Years math teacher has taught high school math | 9.82 | 9.40 | 8.47 | 8.04 |
| Years math teacher has taught any subject to grade levels K-8 | 3.76 | 5.84 | 2.67 | 5.32 |
| Years math teacher has taught any subject to grade levels 9-12 | 10.10 | 9.43 | 9.62 | 8.11 |
| Years math teacher has taught any subject / grade at current school | 7.77 | 8.78 | 6.64 | 6.29 |
| Years science teacher has taught high school science | 10.14 | 8.94 | 10.28 | 8.63 |
| Years science teacher has taught any subject to grade levels K-8 | 3.23 | 6.14 | 2.70 | 4.87 |
| Years science teacher has taught any subject to grade levels 9-12 | 10.42 | 9.04 | 10.45 | 8.56 |
| Years science teacher has taught any subject/grade at current school | 8.49 | 7.59 | 7.66 | 7.15 |
| Cost-adjusted salary scale* | 5.40 | 1.68 | 3.82 | 0.86 |

*Scale of salary derived by Morgan & Jung (2016) from Common Core of Data. Range of scale is [2.19, 12.10]
*Note:* Remainder of variables drawn from HSLS using data from 2009-2010, e.g. when students were in 9$^{th}$ grade

**Table 8:** Legend for Figure 1's Causal Diagram

| Symbol | Description | |
|---|---|---|
| ○ | Unobserved | |
| ● | Observed | |
| ____ | School-level variable | |
| ____ | Individual-level student variable | |
| ____ | Community & district-level variable | |
| **Node** | **Variable(s)** | **Source** |
| D | Counselor caseload size (Caseload size) | HSLS |
| Y | Student goes to college (Outcome variable) | HSLS |
| F | Intent to apply for financial aid | n/a |
| H | Counselor percentage of time spent on college; Goal prescience | n/a |
| A | GPA; Math achievement in 11$^{th}$ grade | n/a |
| R | SES; Parent is college educated; Member of underrepresented race | HSLS |
| U | District urbanity; Percent of district that is poor; Percent of district that has a bachelor's degree | ACS |
| W | Free-and-reduced lunch percentage of school; White & Asian percentage | CCD |
| G | School's overall college-going rate | n/a |
| S | Knowledge and value of college | n/a |
| B | Expected benefits and costs | n/a |

**Table 9:** Balance of Means and SDs for Matching Covariates with

| | ATT Weights | | | | ATC Weights | | | |
|---|---|---|---|---|---|---|---|---|
| | $D_i = 1$ | | $D_i = 0$ | | $D_i = 1$ | | $D_i = 0$ | |
| Variable | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Parent attended college | 0.30 | 0.46 | 0.29 | 0.46 | 0.29 | 0.46 | 0.34 | 0.47 |
| Underrep race | 0.35 | 0.48 | 0.35 | 0.48 | 0.50 | 0.50 | 0.42 | 0.49 |
| SES | -0.12 | 0.69 | -0.12 | 0.73 | -0.22 | 0.72 | -0.12 | 0.74 |
| Pct FRL | 0.47 | 0.23 | 0.47 | 0.22 | 0.45 | 0.23 | 0.43 | 0.21 |
| Pct White & Asian | 0.64 | 0.33 | 0.63 | 0.30 | 0.51 | 0.36 | 0.59 | 0.29 |
| Urban area* | 0.23 | 0.42 | 0.24 | 0.43 | 0.27 | 0.44 | 0.29 | 0.45 |
| Pct poor* | 0.15 | 0.08 | 0.15 | 0.07 | 0.18 | 0.09 | 0.16 | 0.07 |
| Pct with bach degree* | 0.26 | 0.12 | 0.26 | 0.12 | 0.24 | 0.13 | 0.26 | 0.11 |
| *Mean Abs Diff* | 0.02 (0.06) | | | | 0.15 (0.10) | | | |

n = 15,751 for $D_i = 1$ and $D_i = 0$

**Table 10:** Balance of Means and SDs for Matching Covariates with Datamined weight

| | ATT Weights | | | | ATC Weights | | | |
|---|---|---|---|---|---|---|---|---|
| | $D_i = 1$ | | $D_i = 0$ | | $D_i = 1$ | | $D_i = 0$ | |
| Variable | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Parent attended college | 0.30 | 0.46 | 0.32 | 0.47 | 0.34 | 0.47 | 0.34 | 0.47 |
| Underrep race | 0.35 | 0.48 | 0.33 | 0.47 | 0.42 | 0.49 | 0.42 | 0.49 |
| SES | -0.12 | 0.69 | -0.11 | 0.67 | -0.13 | 0.81 | -0.13 | 0.74 |
| Pct FRL | 0.47 | 0.23 | 0.46 | 0.24 | 0.44 | 0.22 | 0.43 | 0.21 |
| Pct White & Asian | 0.64 | 0.33 | 0.65 | 0.31 | 0.57 | 0.33 | 0.59 | 0.29 |
| Urban area* | 0.23 | 0.42 | 0.23 | 0.42 | 0.24 | 0.43 | 0.29 | 0.45 |
| Pct poor* | 0.15 | 0.08 | 0.15 | 0.07 | 0.16 | 0.09 | 0.16 | 0.07 |
| Pct with bach degree* | 0.26 | 0.13 | 0.26 | 0.13 | 0.25 | 0.13 | 0.26 | 0.11 |
| *Mean Abs Diff* | 0.02 (0.04) | | | | 0.07 (0.09) | | | |

n = 8,811 for $D_i = 1$ and 14,851 for $D_i = 0$

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