RAND EDUCATION AND LABOR

Connecting College Students to Alternative Sources of Support

Technical Appendix

Lindsay Daugherty, William R. Johnston, Tiffany Berglund

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Introduction

This technical appendix serves several purposes. First, it provides some additional details about the data used in the report *Connecting College Students to Alternative Sources of Support: The Single Stop Community College Initiative and Postsecondary Outcomes* (Daugherty, Johnston, and Tsai, 2020). Second, presenting effect sizes for our results provides a metric that allows us to compare the estimated relationship between Single Stop use and student outcomes with other interventions that aim to improve college outcomes. Finally, we present findings from multiple comparison adjustments for the estimates produced to address our confirmatory research question.

Note that this is an updated version of the technical appendix, first published in 2017. A secondary detailed review indicated that some refinements were needed in Tables A.1 through A.5, although though those changes did not substantively affect the findings.

Additional Details on Data

Control Variables

The report used two methodologies: multiple regression analysis and coarsened exact matching (CEM). The controls in both approaches were gender, age, race and ethnicity, high school GPA, first in family to attend college, campus of attendance, household income, financial aid receipt, dependency status, and whether the student has dependents.

Missing Data

We encountered missing data for some of our variables that had to be accounted for in the analysis. Table A.1 presents the percentage of students with missing data for each of our control variables. We had full data for all of our variables except for those related to financial aid or drawn from missing financial aid forms. More than a fifth of students were missing data drawn from financial aid forms because a substantial portion of students do not apply for federal financial aid and therefore have not provided this information to institutions. Financial aid receipt was a separate variable that was reported by institutions as opposed to drawn from the federal financial aid data, and we did not have any information on why data were missing for approximately 5 percent of our sample.

In our regression analysis, we created a missing data indicator variable for each of our control variables that was equal to 0 if a student did have data for the field and 1 if the student did not have data for the field. We then set values for the control variable equal to 0 for all individuals with missing data. This allowed us to retain all students in the analysis regardless of whether they were missing data. Rather than imputing data or making assumptions about the possible values the missing data might have, this approach restricted comparisons of Single Stop users with missing data to non–Single Stop users with missing data. In our CEM analysis, students with missing data were assigned to their own "missing data" bin for each covariate where data was missing, and Single Stop users were matched to other non–Single Stop users within that bin of students with missing data. This is the equivalent to what was done with the multiple regression analysis, where we created a "missing data" indicator to restrict comparisons of Single Stop users who had missing data for a covariate with other non–Single Stop users who were also missing data.

Table A.1. Percentage of Students with Missing Data, by Variable

Variable	Percentage of Sample Missing
Gender	0
Age	0
Race and ethnicity	0
High school GPA	0
First in family to attend college	0
Campus of attendance	0
Financial aid receipt	4.5
Household income	22.1
Dependent status	21.3
Has dependents	21.3

Effect Sizes

While we were able to measure the statistical and practical significance of using Single Stop, our estimates are not directly comparable to other studies of college-going interventions. By placing estimates across a wide range of outcomes and samples on a common scale of standard deviations, effect sizes allow for the comparison of effects across a range of educational interventions that aim to bring about different educational outcomes and serve different populations.

To calculate effect sizes, we use Hedges' *g* (Hedges, 2007) for both persistence and credit outcomes. While the What Works Clearinghouse (WWC) manual recommends different approaches for continuous and dichotomous variables (Hedges' *g* and the Cox Index, respectively), our analytic model for persistence used linear regression, so we determined that it was more appropriate to use the statistic recommended for continuous variables (WWC, 2013). In addition, the Cox Index estimates recommended for dichotomous variables were very similar to those produced with Hedges' *g*. Because we considered our CEM estimates to be our primary estimates, we calculated those effect sizes. Effect sizes for persistence outcomes and credit outcomes are presented in Tables A.2 and A.3.

Table A.2. Effect Sizes for Persistence Estimates

	One-Semester Persistence		One-Year Persistence	
	CEM	Effect Size	CEM	Effect Size
Single Stop user	0.031***	0.102	0.031**	0.061
Benefit screening	0.029***	0.096	0.026*	0.053
Tax service	—	—	0.145***	0.297

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A.3. Effect Sizes for Credit Estimates

	Credits Attempted		Credits Earned		Credits Earned/Attempted	
	CEM	Effect Size	CEM	Effect Size	CEM	Effect Size
Single Stop user	0.384*	0.054	0.371	0.043	–0.000	0.000
Benefit screening	0.299	0.043	0.244	0.029	–0.003	–0.012
Tax service	1.072*	0.128	1.555*	0.170	0.028	0.085

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Multiple-Comparison Correction

Multiple-comparison correction helps to account for the potential for false positives when multiple outcomes are being estimated within the same domain. The procedure involves the comparison of the observed *p*-values and a critical value that is estimated based on the total number of tests being performed within a domain; the critical *p*-value to determine statistical significance (in this case, we use the default value of 0.05); and each observed *p*-value rank, ordered from smallest to largest. The next step is to identify the largest observed *p*-value that is smaller than the critical value. This sets a threshold so that all findings with larger observed *p*-values are no longer significant at the prespecified level of significance.

According to WWC standards (WWC, 2013), multiple comparison adjustments must be conducted for all confirmatory research questions to account for multiple outcomes examined within a single domain. The report describes the following research questions:

1. Is use of Single Stop associated with improved postsecondary outcomes in terms of persistence and credit accumulation?
2. Is use of a public benefit screening associated with improved postsecondary outcomes in terms of persistence and credit accumulation?
3. Is use of tax services associated with improved postsecondary outcomes in terms of persistence and credit accumulation?
4. Do the relationships between Single Stop use and postsecondary outcomes vary across student subgroups?

5. Do the relationships between Single Stop use and postsecondary outcomes vary across institutions?

Only the first research question was listed as confirmatory in the Social Innovation Fund evaluation plan; all others were listed as exploratory. We therefore focused on our estimates of the relationship between Single Stop use and postsecondary outcomes for all Single Stop users. Because we examined two persistence outcomes and three credit outcomes, we followed WWC recommendations by accounting for multiple comparisons within each domain.[1]

To adjust for multiple comparisons, we used the Benjamini-Hochberg (BH) procedure (Benjamini and Hochberg, 1995). The results for persistence outcomes are presented in Table A.4. After correcting for multiple comparisons, we found that both of the persistence outcomes remained statistically significant.[2]

Table A.4. Multiple-Comparison Adjustments for Persistence Outcomes

	Coeff.	Original *p*-Value	*p*-Value Rank	Total # of Tests in Domain	Target *p*-Value	New Critical *p*-Value (0.05*X*/2)	Is Original *p* Smaller Than Critical Value?	Statistical Significance After BH Correction?
One-semester persistence	0.031	0.001	1	2	0.05	0.025	Yes	**Yes**
One-year persistence	0.031	0.001	2	2	0.05	0.05	Yes	**Yes**

The results for credit outcomes are presented in Table A.5. After correcting for multiple comparisons, we found that the previous estimate for credits attempted was no longer statistically significant. The other estimates for credit outcomes were not significant prior to correction.

[1] Technically, only one of the three credit outcomes was listed as confirmatory in the evaluation plan: the ratio of credits earned to credits attempted. Total credits attempted and earned were listed in a separate exploratory question. Therefore, it was not necessary for us to adjust our estimates for credit outcomes for multiple comparisons. However, we decided to present the results for multiple comparisons adjustments for credit variables for the sake of completeness.

[2] Both persistence outcomes would remain statistically significant even if we were to apply a standard that is more rigorous than the WWC recommendations by adjusting for multiple comparisons across, rather than within, outcome domains.

Table A.5. Multiple-Comparison Adjustments for Credit Outcomes

	Coeff.	Original *p*-Value	*p*-Value Rank	Total # of Tests in Domain	Target *p*-Value	New Critical *p*-Value (0.05*X*/2)	Is Original *p* Smaller Than Critical Value?	Statistical Significance After BH Correction?
Credits attempted	0.384	0.05	1	3	0.05	0.017	No	**No**
Credits earned	0.371	0.11	2	3	0.05	0.033	No	**No**
Credit ratio	0.000	0.11	3	3	0.05	0.050	No	**No**

References

Benjamini, Yoav, and Yosef Hochberg, "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing," *Journal of the Royal Statistical Society, Series B (Methodological)*, Vol. 57, No. 1, 1995, pp. 289–300.

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Hedges, Larry V., "Effect Sizes in Cluster-Randomized Designs," *Journal of Educational and Behavioral Statistics*, Vol. 32, 2007, pp. 341–370.

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WWC—*See* What Works Clearinghouse.