

Gauging the Effect of Peer Assisted Learning on STEM Course Outcomes Using Propensity Score Matching

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Overview

- ▶ Assess whether peer-assisted learning (PAL) increases grades in gateway science and math courses
- ▶ Students self-select into PAL, creating potential for bias
- ▶ Use propensity score matching to reduce selection bias
 - ▶ Compare regression estimates to matching estimates

Project PASS (Peer-Assisted Student Success)

- ▶ Goals
 - ▶ Improve grades in gateway STEM courses
 - ▶ Improve student retention
- ▶ Approach
 - ▶ Peer-assisted learning (PAL)
 - ▶ Advising
- ▶ Courses
 - ▶ Initially
 - ▶ Developmental Chemistry (CHEM 4)
 - ▶ Introductory Chemistry (CHEM 1A)
 - ▶ Pre-Calculus (MATH 29)
 - ▶ Calculus (MATH 30)
 - ▶ Additional courses added periodically

Program Structure

Peer-assisted Learning

- ▶ Two-hour/week discussion section focused on problem-solving
- ▶ Led by a student trained in PAL facilitation
- ▶ Faculty create problem worksheets for use in PAL sessions and get feedback from PAL facilitators on where students have difficulties

Advising

- ▶ Students who are on academic probation or who are repeating the course are referred to advising before the beginning of the semester
- ▶ Students who perform poorly on the first exam are referred to advising during the semester

Data Elements

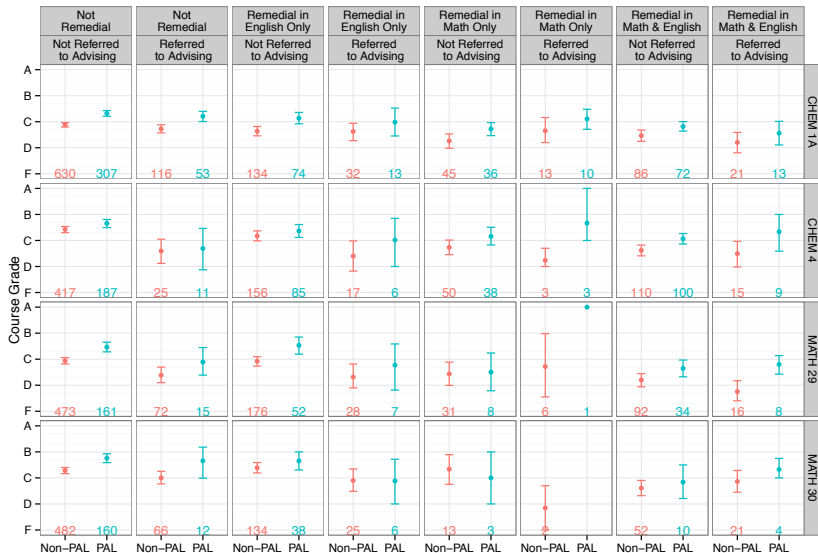
- ▶ All students who took one of four science and math courses during a term when PAL was available
 - ▶ Spring 2012 – Spring 2015 or Fall 2012 – Spring 2015
- ▶ Covariate data
 - ▶ Demographics (age, gender, ethnicity, parents' education, on-campus housing, Pell grant eligibility)
 - ▶ Academics (high school GPA, SAT scores, CSUS GPA, units, class level, major, first-year seminar, AP scores, time between high school and college, remedial status)
- ▶ Analysis performed with the R programming language and the Matchit package for propensity score matching

Sample Profile

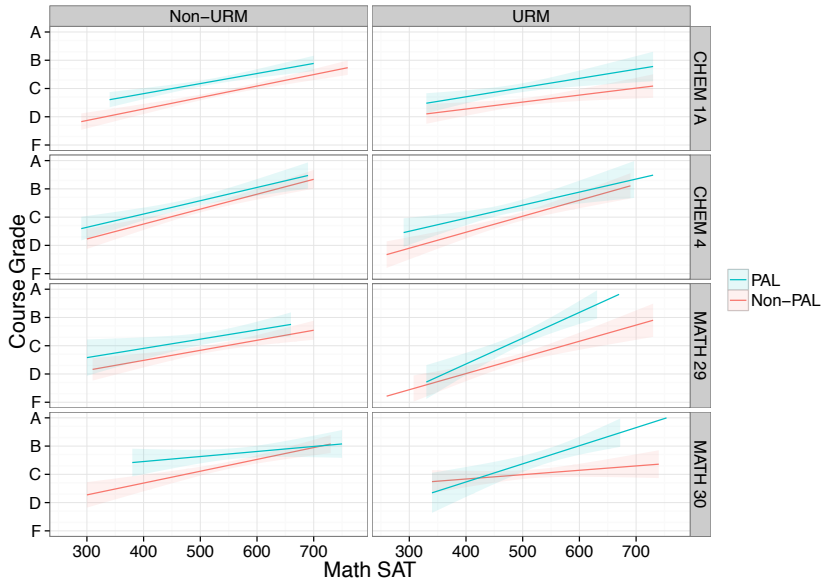
- ▶ Data include all enrollments during the terms when PAL was available for a given course

Course	Enrollments	Unique	PAL %
CHEM 1A	1712	1418	36.3%
CHEM 4	1270	1216	37.0%
MATH 29	1224	1121	25.9%
MATH 30	1061	971	23.5%
Total	5267	3336	31.5%

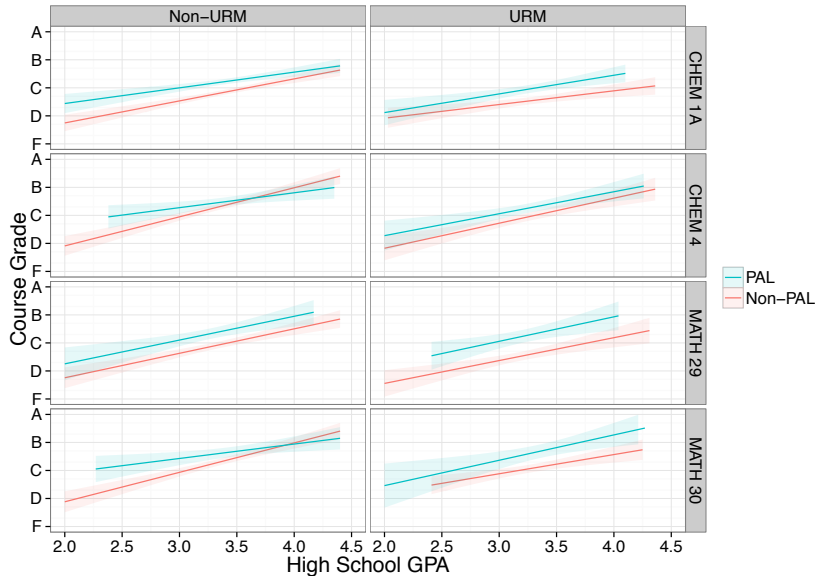
PAL vs. Non-PAL by Remedial Status and PASS Advising Referral



PAL vs. Non-PAL by URM Status and Math SAT



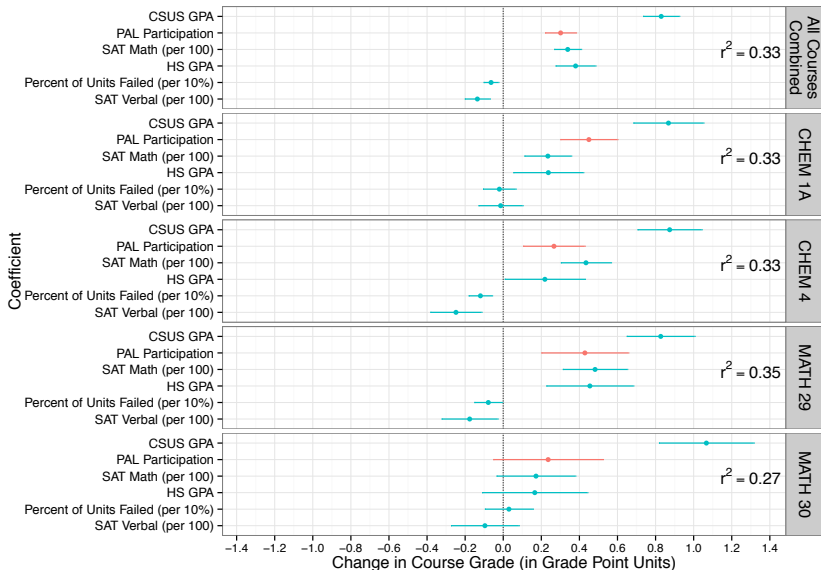
PAL vs. Non-PAL by URM Status and High School GPA



Regression Model Predicting Course Grade

- ▶ Limit to students. . .
 - ▶ Taking course for the first time
 - ▶ No previous PAL participation
 - ▶ Non-missing SAT score and high school GPA
- ▶ 2322 students and 2909 enrollments, or about 70% of all students who took one or more of the four courses during the study period

Predicting Course Grade vs. PAL Participation



Summary So Far

- ▶ PAL participation and course grades
 - ▶ Linear regression of PAL participation vs. course grade suggests, controlling for other factors, PAL students' grades are, on average, about 0.3 grade points higher, when compared with non-PAL students
 - ▶ Models for individual courses suggest PAL students' grades are 0.24 to 0.45 grade points higher, on average, when compared with non-PAL students (coefficient for MATH 30 (Calculus) was not statistically significant)
- ▶ Potential for bias if outcomes are correlated with selection into PAL

Addressing Bias in Observational Studies

- ▶ Random assignment usually not possible for ethical and logistical reasons
- ▶ Try to reduce selection bias in observational data by accounting for factors that predict selection into the treatment
- ▶ Propensity score: Probability of receiving the treatment, given what we know about the study subjects (Rosenbaum and Rubin, 1983)
 - ▶ Estimate with logistic regression (or other classification methods)
 - ▶ Predictors should be related to PAL participation and should either be fixed or measured prior to treatment

Propensity Score Matching

- ▶ Match treated and untreated based on similar propensity scores.
 - ▶ Results in treatment and control groups that have, conditional on the observed factors, a similar probability of being in the treatment group
- ▶ Check for balance of treatment and control groups on the observed covariates
- ▶ Compare means of treated and control subjects (by direct comparison, PS weighting, or regression adjustment)
- ▶ Matching is intended to make treated (PAL students) and untreated (non-PAL students) more like what would have happened with randomized selection
- ▶ Results in more credible inferences regarding causal effects from observational data

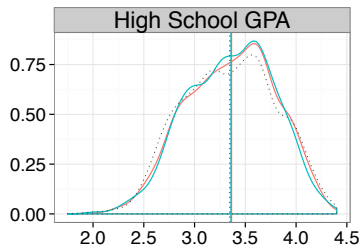
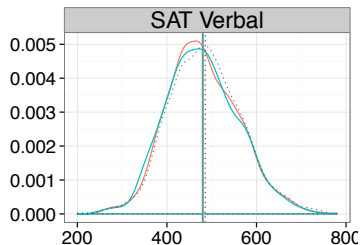
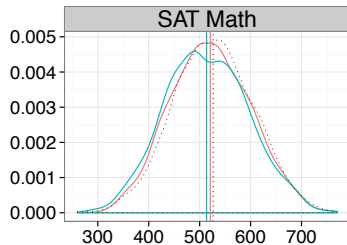
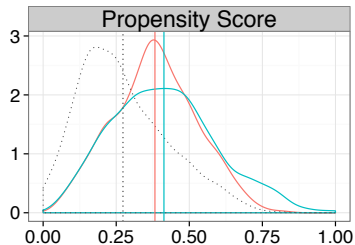
Check Balance After Matching




After Matching

Before Matching

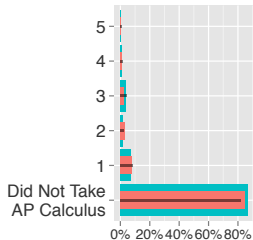
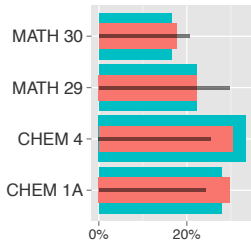
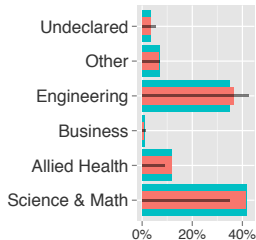
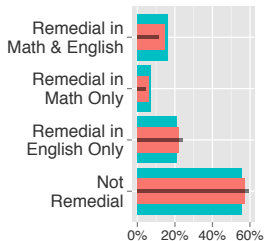
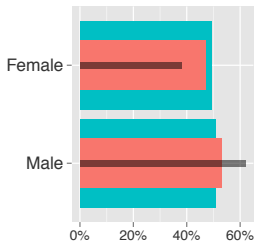
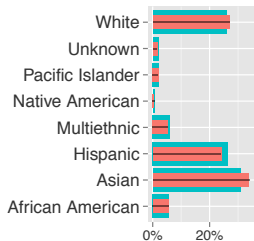
Variable	% Improve	PAL	Non-PAL	Diff	PAL	Non-PAL	Diff
MATH 29	98.70	22.19	22.29	-0.10	22.19	29.72	-7.53
Major: Science & Math	92.40	41.88	41.34	0.54	41.88	34.81	7.07
Undeclared	86.80	3.57	3.35	0.22	3.57	5.24	-1.67
Mother: HS Grad	86.00	46.54	46.32	0.22	46.54	48.11	-1.57
CSUS GPA	85.70	2.99	3.00	-0.00	2.99	2.96	0.03
On-Campus Housing	82.00	25.22	24.78	0.44	25.22	22.77	2.45
Major: Engineering	79.60	34.74	36.36	-1.62	34.74	42.67	-7.93
Male	79.30	50.87	53.14	-2.27	50.87	61.86	-10.99
First-Year Seminar	78.40	8.12	8.01	0.11	8.12	7.61	0.51
Propensity Score	78.00	0.41	0.38	0.03	0.41	0.27	0.14
Pacific Islander	73.20	2.27	2.16	0.11	2.27	1.86	0.41
MATH 30	71.00	16.45	17.64	-1.19	16.45	20.55	-4.10
Units Attempted	69.20	13.80	13.72	0.08	13.80	13.53	0.27
Remedial: Math & English	67.90	16.34	14.83	1.51	16.34	11.64	4.70
SAT Verbal	67.30	479.24	481.31	-2.07	479.24	485.57	-6.32
Age	67.20	19.55	19.52	0.03	19.55	19.63	-0.09
Remedial: Math Only	64.20	7.14	6.28	0.86	7.14	4.74	2.40
Not Remedial	62.40	55.63	57.03	-1.40	55.63	59.35	-3.72
CHEM 4	60.50	33.44	30.30	3.14	33.44	25.49	7.95
CHEM 1A	50.10	27.92	29.76	-1.84	27.92	24.23	3.69
HS GPA	48.90	3.36	3.36	-0.01	3.36	3.35	0.01
SAT Math	43.40	513.58	520.89	-7.31	513.58	526.49	-12.91
Yrs betw HS and Coll	23.90	0.11	0.09	0.02	0.11	0.13	-0.02
Asian	12.40	30.84	33.66	-2.82	30.84	34.06	-3.22
Hispanic	11.60	26.41	24.13	2.28	26.41	23.83	2.58
AP Calculus	-2.60	2.71	2.70	0.02	2.71	2.70	0.02
White	-10.20	25.87	27.06	-1.19	25.87	26.95	-1.08
African American	-340.00	5.74	5.52	0.22	5.74	5.79	-0.05
Freshman	-690.90	49.68	48.81	0.87	49.68	49.57	0.11

Visual Balance Check: Continuous Variables

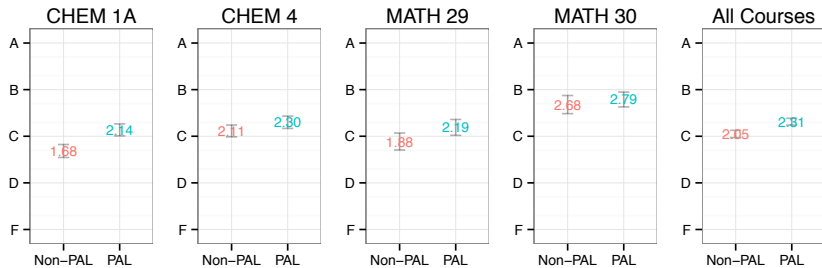


 PAL  Matched Non-PAL  All Non-PAL

Visual Balance Check: Categorical Variables



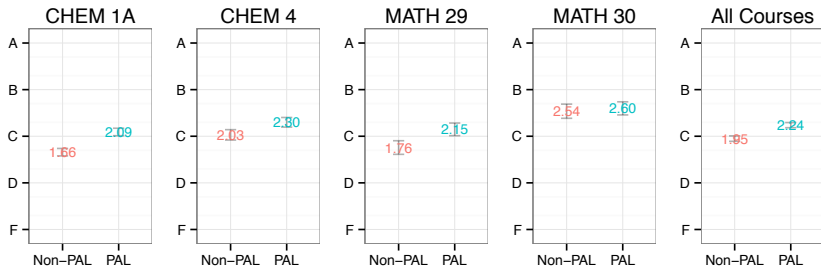
Average Course Grade by PAL Participation: Matched Comparison



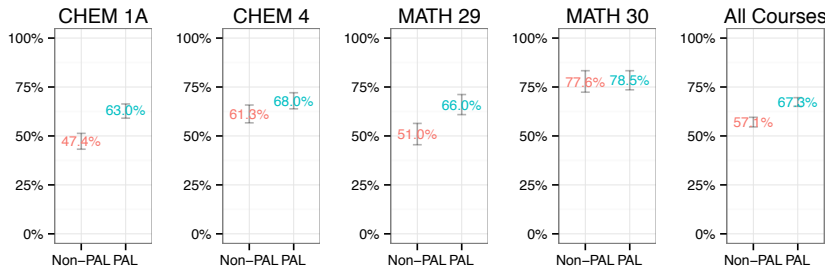
Course	Matching	Regression	Diff
All Courses Combined	0.26	0.30	-0.04
CHEM 1A	0.46	0.45	0.01
CHEM 4	0.19	0.27	-0.07
MATH 29	0.31	0.43	-0.12
MATH 30	0.11	0.24	-0.13

Matching on the Full Sample of Students

- ▶ Same process as before, but including students with course repeats and previous PAL courses
 - ▶ Include repeats and previous PAL in the propensity score model



Percent of Students Earning Grade of C or Better



Discussion and Conclusions

- ▶ PAL participation appears to increase students' grades in chemistry and pre-calculus. PAL calculus students' average grade was only slightly higher and difference was not statistically significant.
- ▶ Estimated PAL effect is smaller after propensity score matching (although CHEM 1A was an exception) suggesting some bias in selection into PAL
- ▶ No detectable change in overall course grades or pass rates since implementation of PAL
 - ▶ Potential explanations
 - ▶ Too few students in PAL to cause detectable overall change
 - ▶ Analysis overstates PAL effect despite matching to control for selection bias
 - ▶ Faculty curve grades
 - ▶ Faculty increase course rigor when student performance improves

References

P. Rosenbaum and D. Rubin, "The central role of the propensity score in observational studies for causal effects," *Biometrika*, vol. 70, no. 1, pp. 41-55 (1983)

S. Herzog, "The Propensity Score Analytical Framework: An Overview and Institutional Research Example," *New Directions for Institutional Research*, no. 161, pp. 21-40 (2014)