Exploring the Effect of Supplemental Instruction on Equity Gaps: Student

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Definitions

Two common measurements universities use to identify historically underserved students are underrepresented minority and first generation.

- **Underrepresented Minority (URM)** - is defined as a U.S. citizen who identifies as Black/African American, Hispanic/Latino, or American Indian. All other Race/Ethnicity categories or Non-U.S. citizens are considered as a Non-Underrepresented Minority (Non-URM).
- **First generation** - is defined as a student who reported both parents as not receiving a baccalaureate degree. All other students are considered as Not First Generation

Original Source Data (via CSU Chico Instituional Research)

- Course Detail.csv
  - n = 43,803
  - Row contains record for course sections from Fall 2012 to Winter 2022
- Student Profile Metric.csv
  - n = 49,107
  - Row contains one record per student matriculation for students enrolled from Fall 2012 to Spring 2022
- Student Program.csv
  - n = 343,781
  - Row contains records for each semester of each student's attendance who were enrolled from Fall 2012 to Winter 2022

Original Source Datasets (acquired via CSU Cico Instituional Research)

- SLC Appointment.csv
  - n = 78,229
  - Row contains record for each day that a student went to an SI session, and how many they went to in that day (Fall 2015 - Spring 2022)
- Student Grade.xlsx
  - n = 864,471
  - Row contains final grade data earned for each course for each student from Fall 2016 to Winter 2022

Data Preparation

Student Level Analysis (n = 19,565)

- Only student records dated 2016 or later
- Only first-time freshmen
- Best attempt at isolating most recent student program record
- Approximately 35% of students in the programs dataset are not present in the profiles dataset. Therefore, these records have missing data for HS/Transfer GPA, one-year retention, and matriculation/graduation terms
- Records with missing data for the following attributes were dropped:
  - High School GPA
  - Attended Orientation Flag
  - STEM Major Flag
  - Full Time / Part Time Code
  - Academic Program

Data Preparation

Course Level Analysis (n = 5,637)

- Includes class size, average high school GPA, % first-gen in the class, % URM in the class, DWF rate, SI component flag, term year
  - These were calculated using the grades data provided by IR
  - Students with missing records for high school GPA were not included in the calculation
  - Students with missing records for URM and first-gen status were considered as not a member of these groups
- Course records from 2016-2019
- Course sections with less than 10 records of an SI visit during the semester were considered as sections without an SI-component
- Courses represented have a number less than 300 and are not a special number (x89, x99, etc.)
- To remove high calculated DWF outliers, class size $>= 20$

Data Preparation

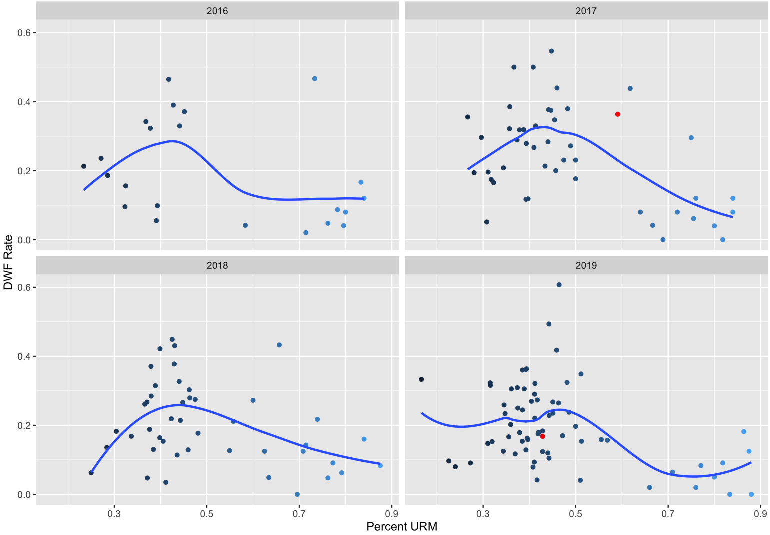
Coarsened Exact Matching Analysis (n = 19,565)

- Student profiles, programs, and grades with course level information for courses with SI
- Only student records dated 2016 to 2019 who DID NOT DROP
- Best attempt at isolating most recent student program record
- Approximately 35% of students in the programs dataset are not present in the profiles dataset. Therefore, these records have missing data for HS/Transfer GPA, one-year retention, and matriculation/graduation terms
- Records with missing data for the following attributes were dropped:
  - High School GPA
  - Attended Orientation Flag
  - STEM Major Flag
  - Full Time / Part Time Code
  - Academic Program

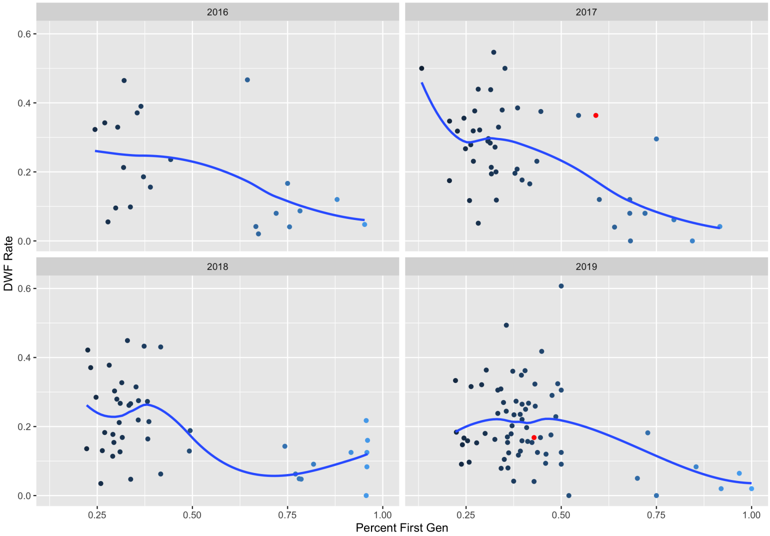
Course Level Details

- Variables of interest:
  - Avg HS GPA
  - First Gen %
  - URM %
  - class size
  - DWF rate
  - class average
  - SI component flag
  - term year
- Courses from term years 2016-2019
- Lower Division courses
- Course sections with class size 20+

URM and DWF Rate



First Generation and DWF Rate



Course Level Modeling

Table 1: Results Multilinear Regression

	Dependent variable:
	dwf.rate
SI.Component.Flag1	0.008 (0.005)
URM	-0.010^{**} (0.005)
First.Gen.Perc	0.009 (0.006)
class.size	-0.0001^{**} (0.00002)
class.average	-0.174^{***} (0.001)
Constant	0.626^{***} (0.004)
Adjusted R^2	0.741
F Statistic	$3{,}231.362^{***}$ (df = 5; 5631)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Course Level Modeling

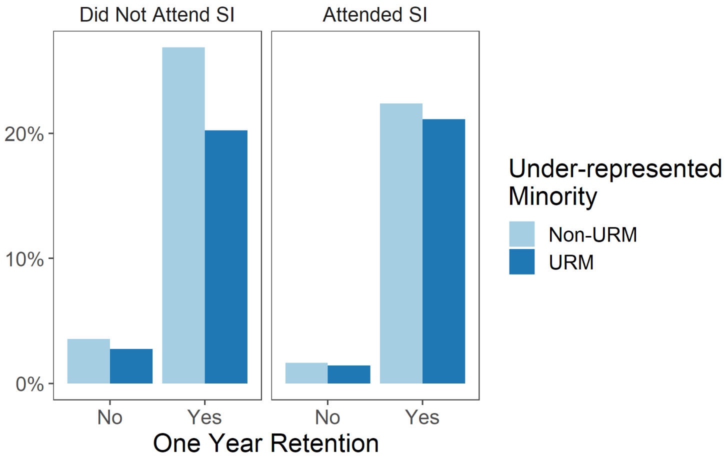
Table 2: Results Multilinear Regression With Interactions

	Dependent variable:
	dwf.rate
SI.Component.Flag1	0.041^{***} (0.014)
URM	-0.012^{**} (0.005)
First.Gen.Perc	0.012^{**} (0.006)
class.size	-0.0001^{***} (0.00002)
class.average	-0.174^{***} (0.001)
SI.Component.Flag1:URM	0.021 (0.044)
SI.Component.Flag1:First.Gen.Perc	-0.096^{***} (0.037)
Constant	0.626^{***} (0.004)
Adjusted R^2	0.742
F Statistic	$2{,}314.955^{***}$ (df = 7; 5629)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Student Level Analysis

- Measuring student level equity gaps
  - Students who under represented minorities
  - Students who are first generation
- Measuring success
  - One-year retention
- First time freshmen matriculated 2016 or later

Student Level Analysis

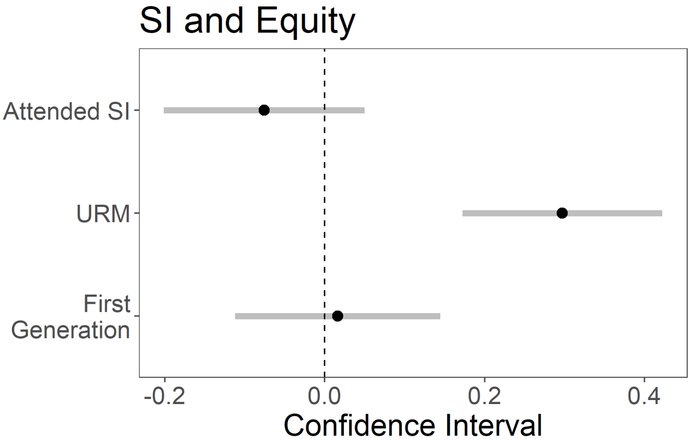


Student Level Analysis

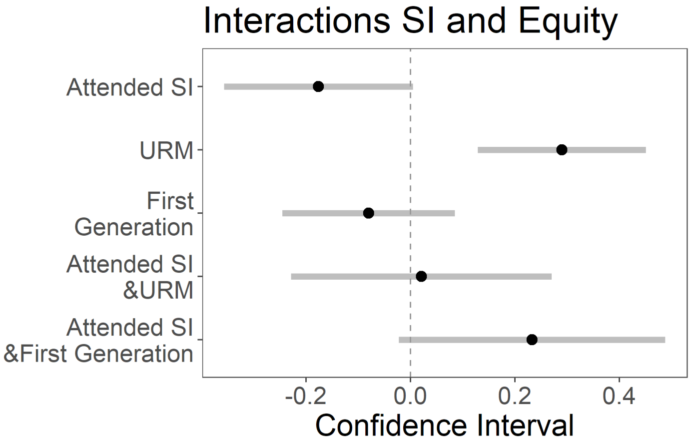
Student Level Analysis: Modeling

- Logistic regression
- Explanatory variables:
  - Student characteristics: URM, First Generation, Gender, Stem Major, number of units taken in the semester, number of units passed in the semester, Cohort term year, SI attendance
  - Course characteristics: Academic level, Course fee existence, GE class
  - Primary variables of interest: SI, URM, First generation, and interactions

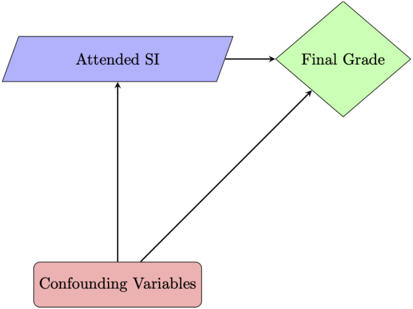
Student Results



Student Results: Interactions



Causal Inference

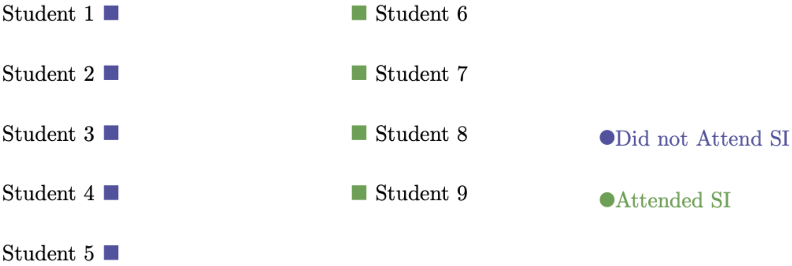


- We want to measure the impact SI has on student performance.
- We need to control for these confounding variables!
- We can accomplish this by matching students with similar characteristics.

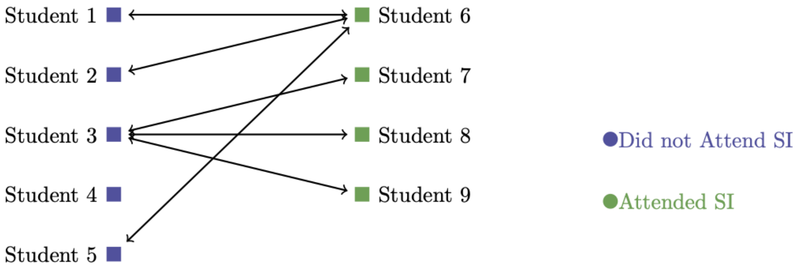
How do we match?

- The goal of matching is to balance the distribution of the covariates
- In order to create the matching, covariates with more than 2 levels are coarsened
  - Coarsening a covariate is essentially binning.
  - After coarsening we match exactly.
  - Lastly, throw out any unmatched observations

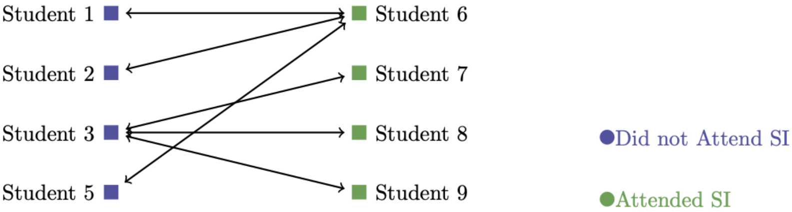
Controlling for Confounding with Coarsened Exact Matching



Controlling for Confounding with Coarsened Exact Matching



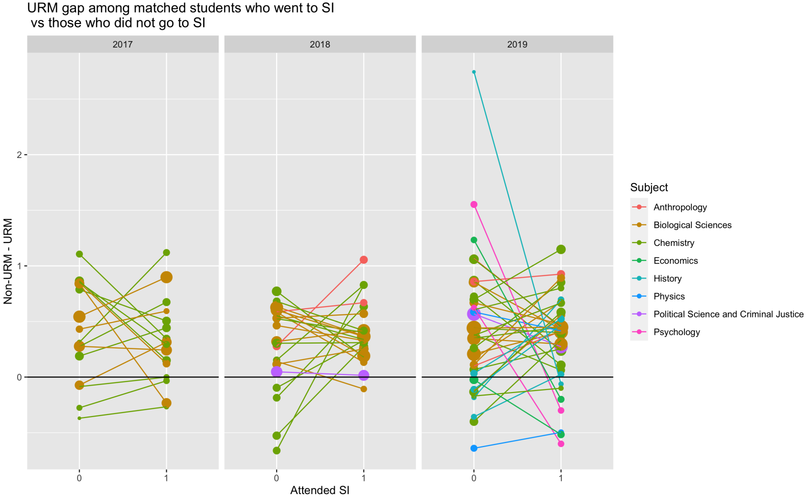
Controlling for Confounding with Coarsened Exact Matching



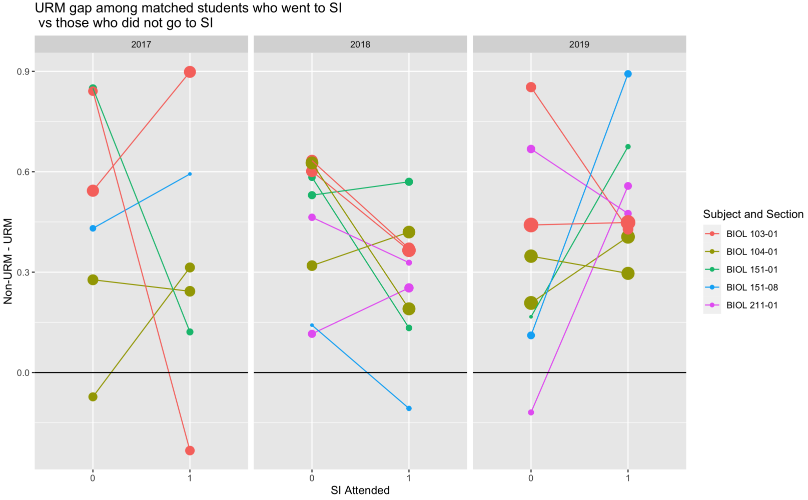
Covariates for Matching

- Notion: Good students go to SI, so the benefit is inflated.
  - High School GPA
  - Student Orientation Flag
  - Major Stem Flag
- Demographics
  - Random Course ID
  - Academic Level
- Equity Gaps
  - First Generation Flag
  - URM/NonURM Flag
  - Gender Code

Visualizing the Equity Gap



Visualizing the Equity Gap



Effect of SI in General

- After creating our matching, we fit a linear model to estimate the effect SI has on a students final grade.
  - The model includes the covariates used in our matching.
- We find, after controlling for our confounding variables, SI improves students final grade by half of a letter grade.
  - This doesn't address the question of whether or not SI reduces equity gaps.

Limitations

- We have no data on student living situations.
  - Are they paying rent or living with parents?
  - Are parents helping with tuition?
  - Are they working full/part time.
- The Oroville dam flooding and Camp fire are not being accounted for.
- We are treating equity gaps separtely.

Next Steps

- Meet with an expert in Casual Inference.
- Can we extended Causal Inference Techniques to account for equity gaps?
  - Can we find trends using difference of proportion plots.
- Can we put dollar amount on the benefit of SI by extending the results of the Casual Inference analysis.
  - Logistic model on matched sample for DWF rates.