

# Exploring the Effect of Supplemental Instruction on Equity Gaps: Student

Faith Fatchen, Skip Moses, Rica Rebusit, Joseph Shifman

5/17/2022

# Original Source Data (via CSU Chico Institutional 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 Institutional 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  $\geq 20$

# Data Preparation

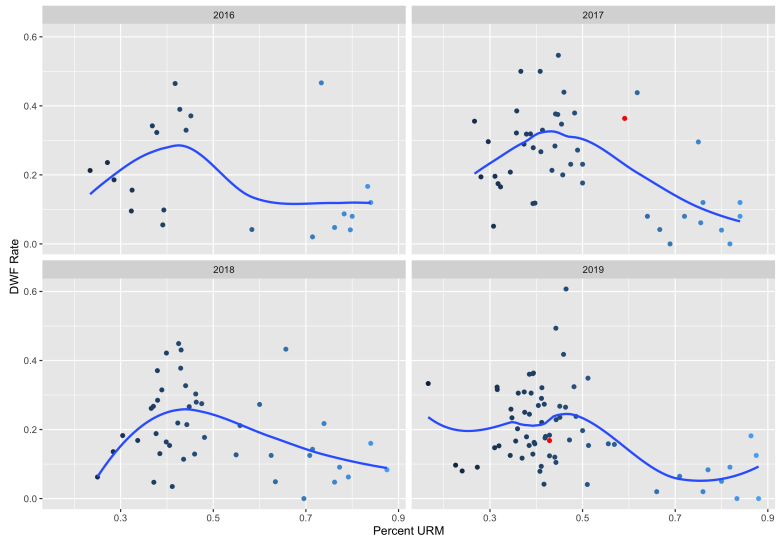
## Coarsened Exact Matching Analysis ( $n = 19,565$ )

- ▶ 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
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  - ▶ Full Time / Part Time Code
  - ▶ Academic Program

## Course Level Details

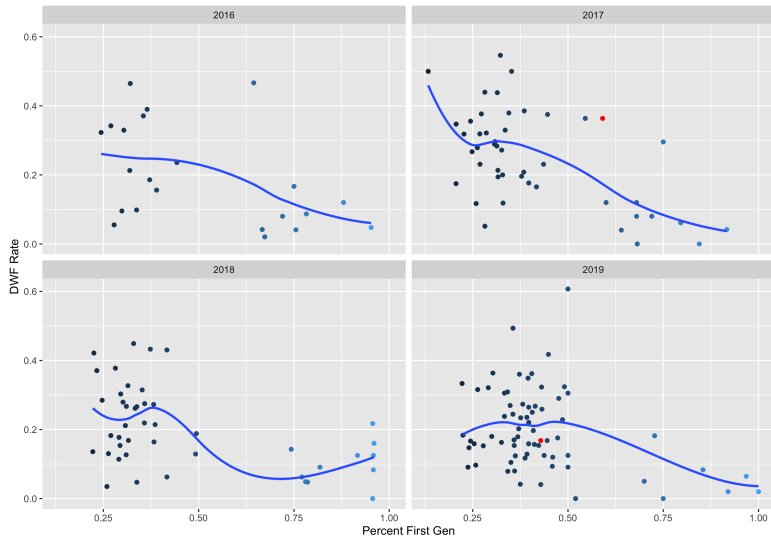
- ▶ Variables: avg HS GPA, First Gen, URM, class size, DWF rate, class average, SI component, term year
- ▶ Courses from term years 2016-2019
- ▶ URM and First Generation percentages
- ▶ Lower Division courses
- ▶ Courses with class size 20+

# URM and DWF Rate





# First Generation and DWF Rate



# Course Level Modelling

Table 1: Results Multilinear Regression

|  | <i>Dependent variable:</i>  |
|--|-----------------------------|
|  | dwf.rate                    |
| Sl.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 <sup>2</sup>                  | 0.741                       |
| F Statistic                              | 3,231.362*** (df = 5; 5631) |
| <i>Note:</i> *p<0.1; **p<0.05; ***p<0.01 |                             |

## Course Level Modelling

Table 2: Results Multilinear Regression With Interaction

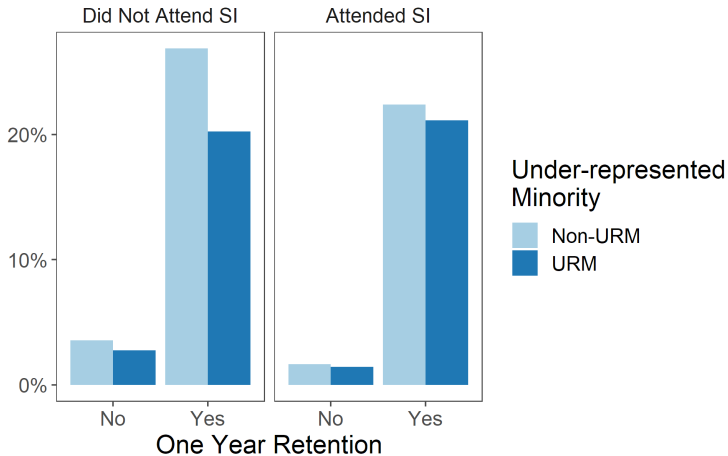
|                                   | <i>Dependent variable:</i>  |
|-----------------------------------|-----------------------------|
|                                   | dwf.rate                    |
| SI.Component.Flag1                | 0.041*** (0.014)            |
| URM                               | −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 <sup>2</sup>           | 0.742                       |
| F Statistic                       | 2,314.955*** (df = 7; 5629) |

Notes: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

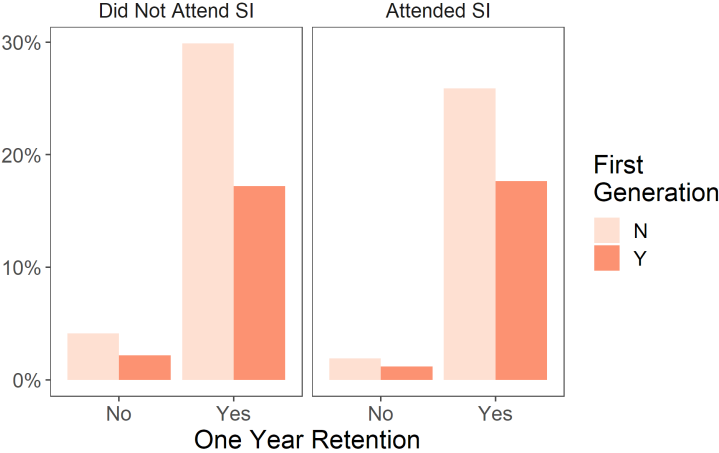
# Student Level Analysis

- ▶ Measuring student level equity gaps
  - ▶ Students who under represented minorities
  - ▶ Students who are first generation
- ▶ Measuring success
  - ▶ One-year retention

# Student Level Analysis



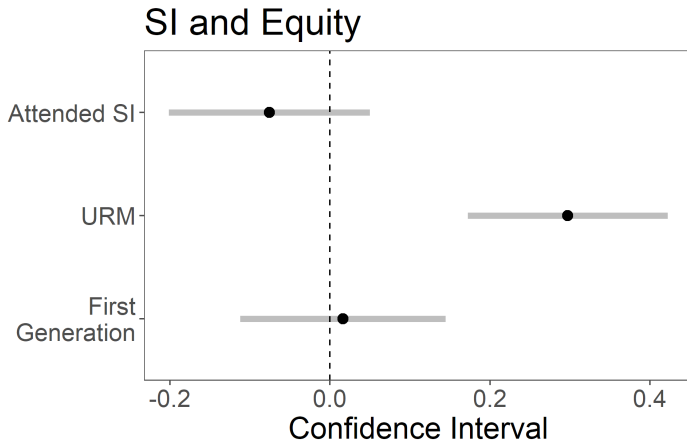
# Student Level Analysis



# Student Level Analysis: Modeling

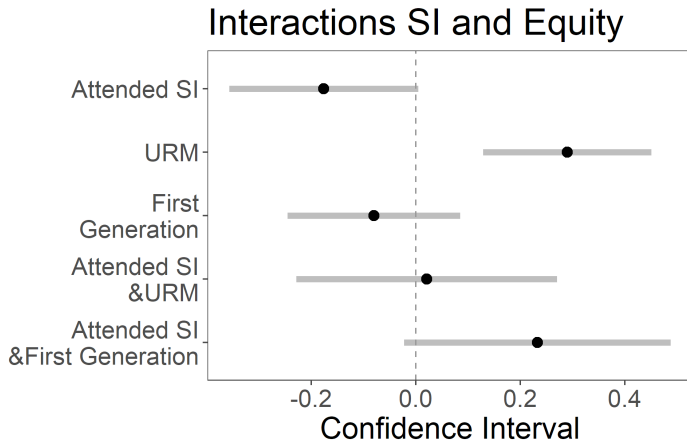
- ▶ Logistic regression
- ▶ Explanatory variables:
  - ▶ Student characteristics: URM, First Generation, Gender, Stem Major, number of units taken in the semester, number of units passed in the semester, Cohort term year, SI attendance
  - ▶ Course characteristics: Academic level, Course fee existence,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

# Student Results

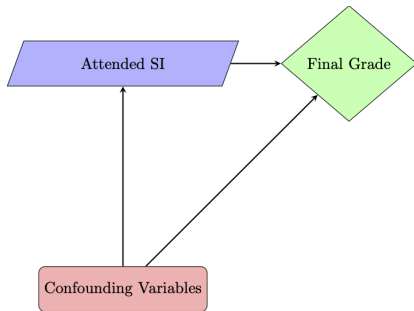




# Student Results: Interactions



# 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?

- ▶ We can't match exactly!
- ▶ We coarsen our covariates (think binning).
- ▶ We can now match exactly on our coarsened data.
- ▶ Lastly, throw out any unmatched observations

# Controlling for Confounding with Coarsened Exact Matching

Student 1 ■

Student 2 ■

Student 3 ■

Student 4 ■

Student 5 ■

■ Student 6

■ Student 7

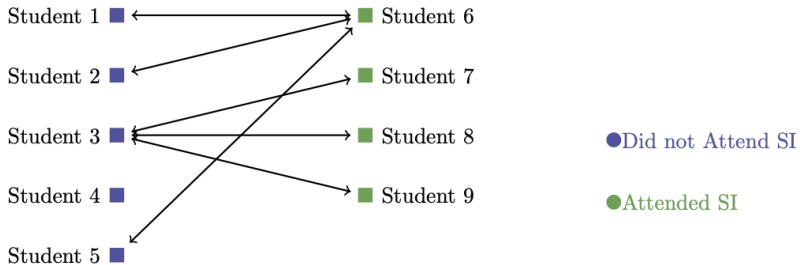
■ Student 8

■ Student 9

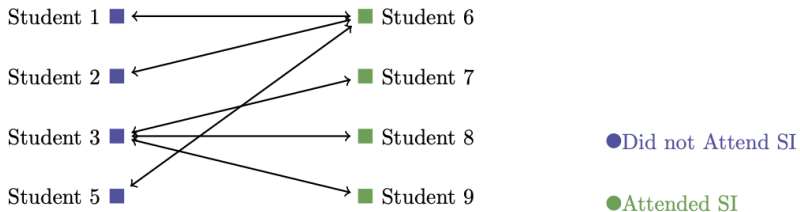
● Did not Attend SI

● Attended SI

# Controlling for Confounding with Coarsened Exact Matching



# Controlling for Confounding with Coarsened Exact Matching

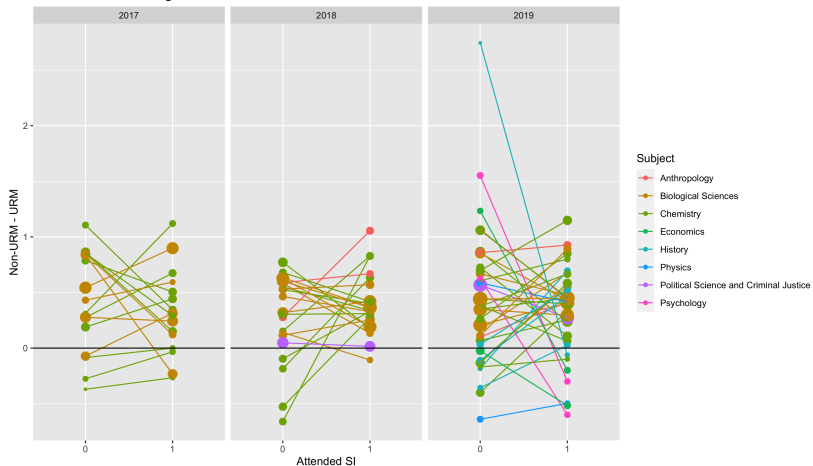


# Covariates for Matching

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

# Visualizing the Equity Gap

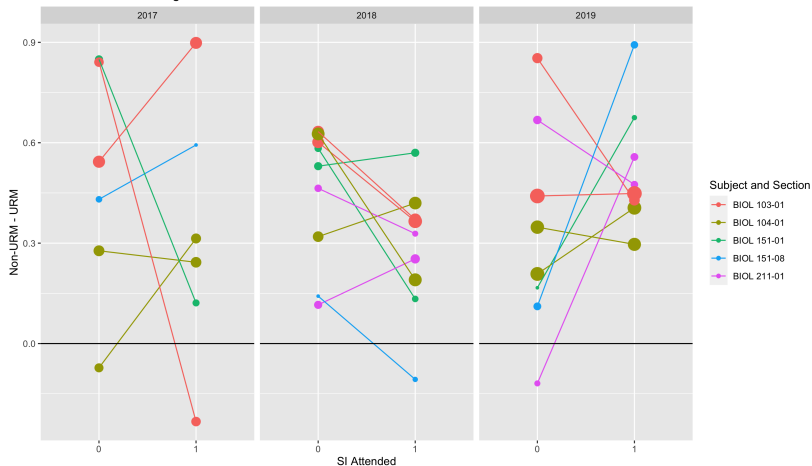
URM gap among matched students who went to SI  
vs those who did not go to SI





# Visualizing the Equity Gap

URM gap among matched students who went to SI  
vs those who did not go to SI



## 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.
- ▶ 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.
- ▶ The Oroville dam flooding and Camp fire are not being accounted for.
- ▶ We are treating equity gaps separately.

## Next Steps

- ▶ Meet with an expert in Casual Inference.
- ▶ Can we extended Causal Inference Techniques to account for equity gaps?
- ▶ Can we put dollar amount on the benefit of SI by extending the results of the Casual Inference analysis.