CALIFORNIA STATE UNIVERSITY
SAN BERNARDINO

Using Multilevel Modeling to Evaluate a Fully-Scaled Summer Bridge Program

41st CAIR Annual Conference, Los Angeles, California

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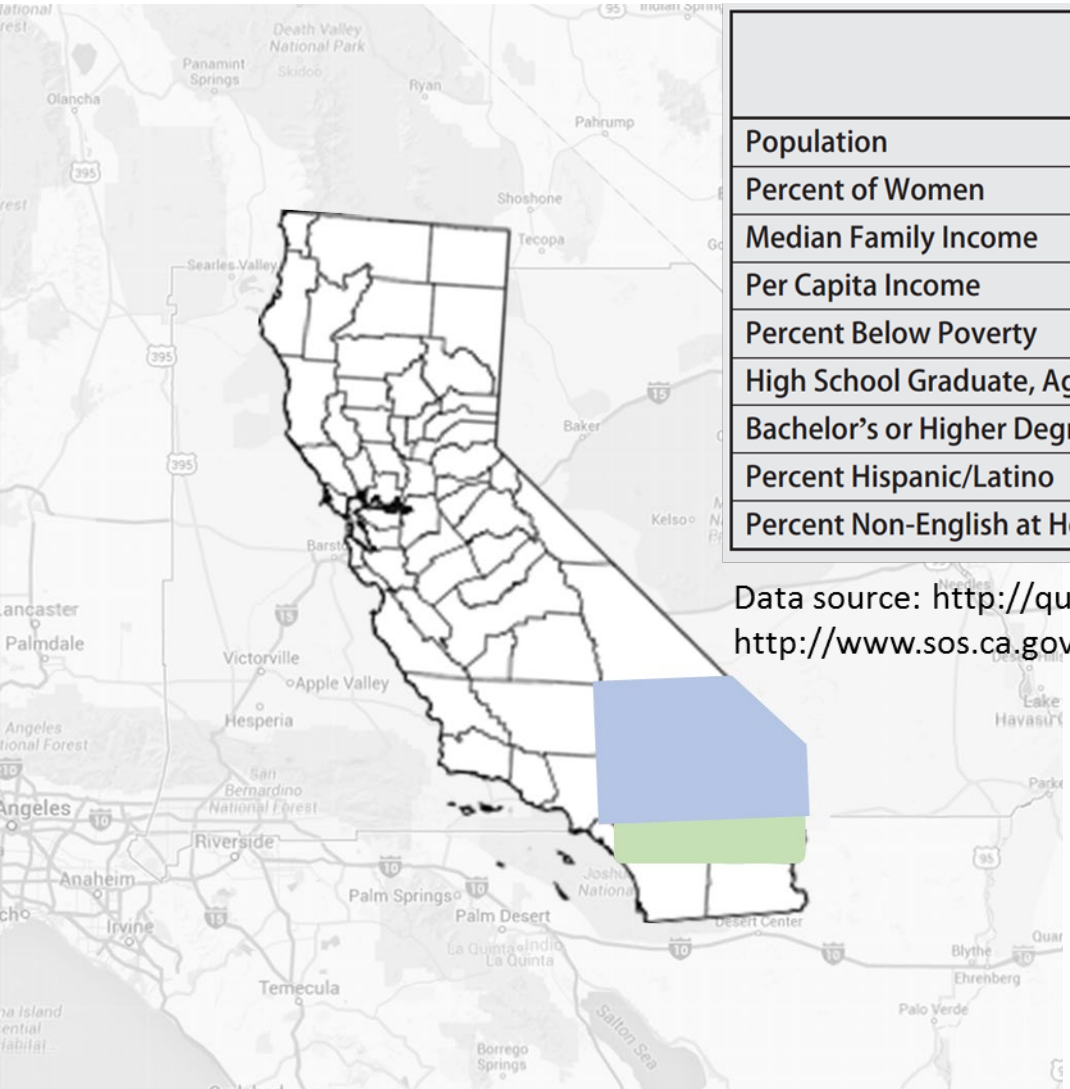
Outline

- CSUSB at a Glance
- Coyote First STEP
  - Program overview
  - Assessment plan
- College-level math analysis
  - Overview of multilevel modeling
  - Study design, research questions
  - Findings
- Discussion

Serving the Inland Empire



	San Bernardino County	Riverside County	California
Population	2,088,371	2,292,507	38,332,521
Percent of Women	50.2%	50.2%	50.3%
Median Family Income	$54,750	$57,096	$61,400
Per Capita Income	$21,636	$23,863	$29,551
Percent Below Poverty	17.6%	15.6%	15.3%
High School Graduate, Age 25+	78.0%	79.2%	81.0%
Bachelor's or Higher Degree	18.6%	20.5%	30.5%
Percent Hispanic/Latino	51.1%	46.9%	38.4%
Percent Non-English at Home	41.0%	39.8%	43.5%

Data source: http://quickfacts.census.gov/qfd/states/06000.html
http://www.sos.ca.gov/elections/ca-map-counties.htm

Fall 2016 Freshmen

Pell Grant Recipients

61%

First Generation

Parents no college: 54%

Parents no Bachelors: 80%

Gender

61%

39%

Ethnicity

71%

Hispanic/Latino

Retention and Graduation

Two-year retention: 85%

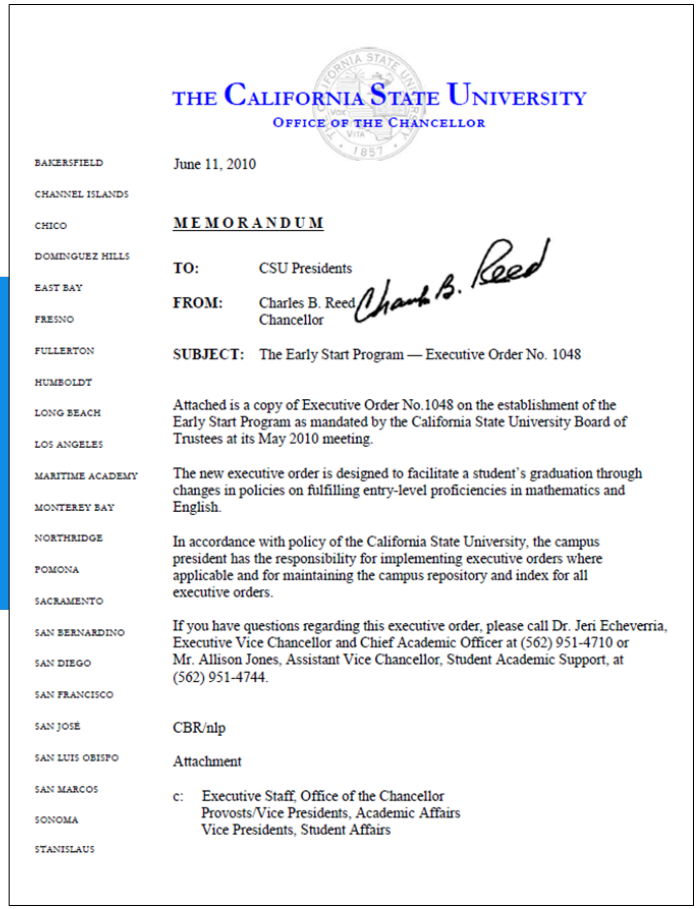
Four-year grad: 11%

Six-year grad: 54%

- First-Time Full-Time Freshmen: 2,791
- Total Enrollment: 20,767

CSU Early Start Mandate

Executive Order No. 1048



THE CALIFORNIA STATE UNIVERSITY
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June 11, 2010

MEMORANDUM

TO: CSU Presidents

FROM: Charles B. Reed
Chancellor

SUBJECT: The Early Start Program — Executive Order No. 1048

Attached is a copy of Executive Order No.1048 on the establishment of the Early Start Program as mandated by the California State University Board of Trustees at its May 2010 meeting.

The new executive order is designed to facilitate a student's graduation through changes in policies on fulfilling entry-level proficiencies in mathematics and English.

In accordance with policy of the California State University, the campus president has the responsibility for implementing executive orders where applicable and for maintaining the campus repository and index for all executive orders.

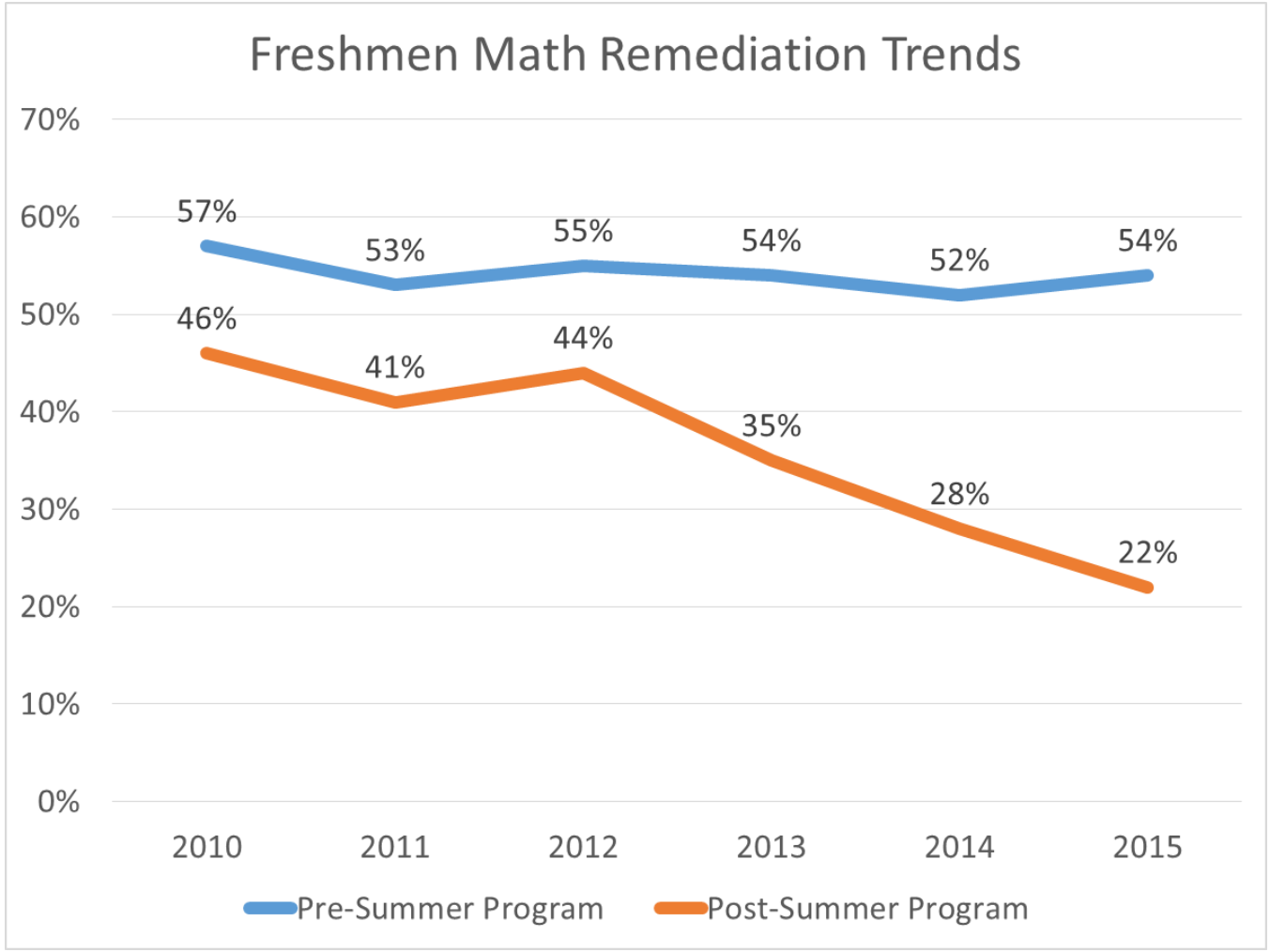
If you have questions regarding this executive order, please call Dr. Jeri Echeverria, Executive Vice Chancellor and Chief Academic Officer at (562) 951-4710 or Mr. Allison Jones, Assistant Vice Chancellor, Student Academic Support, at (562) 951-4744.

CBR/nlp

Attachment

c: Executive Staff, Office of the Chancellor
Provosts/Vice Presidents, Academic Affairs
Vice Presidents, Student Affairs

CSUSB's Math Remediation Trend



Coyote First STEP

4-Week Summer Residential Program

Lecture

Tutoring

CSUSB

Coyote First STEP

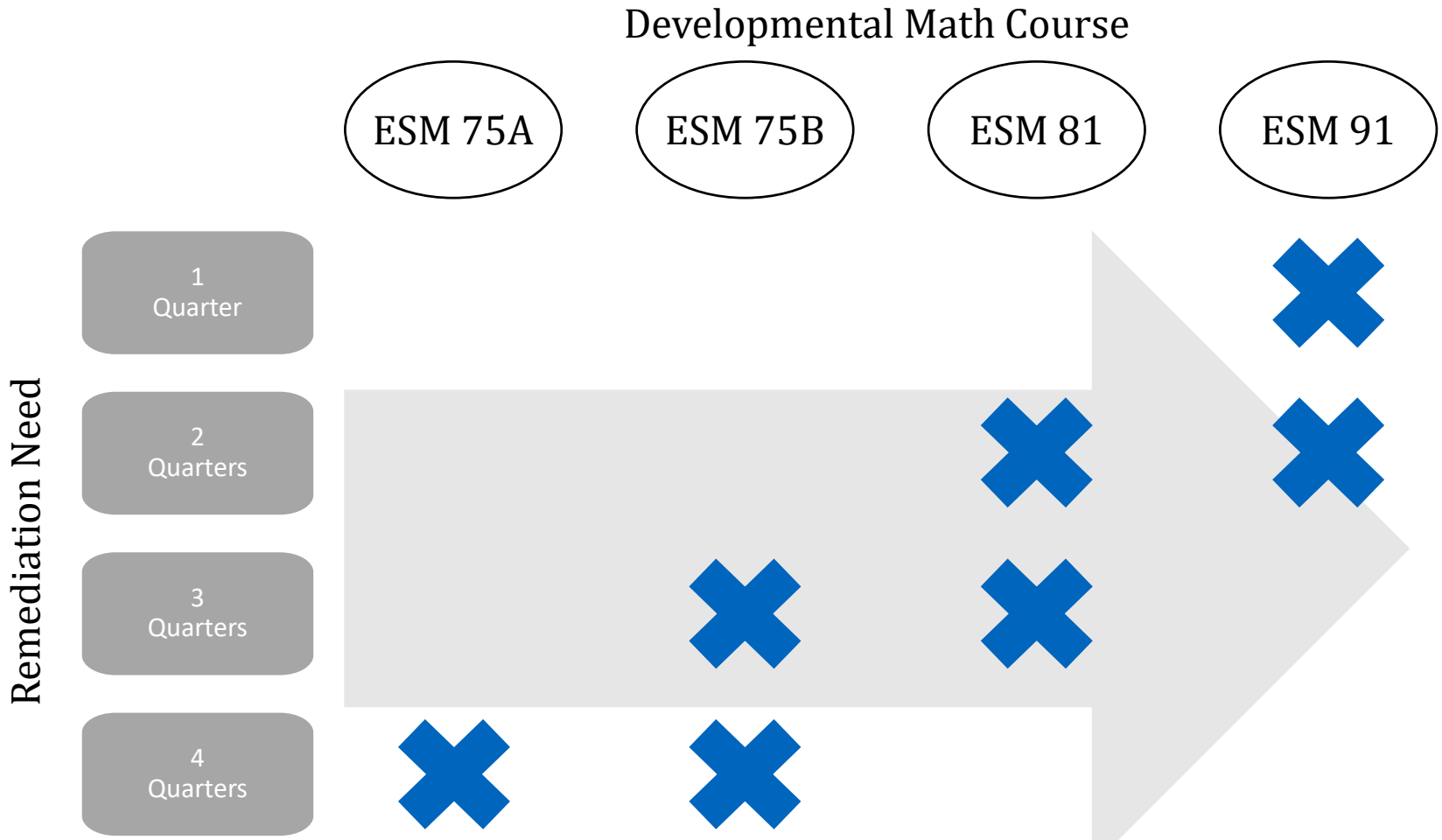
Co-Curricular Programming

FREE

for all 1,517 students

Mandatory (Fully-Scaled)

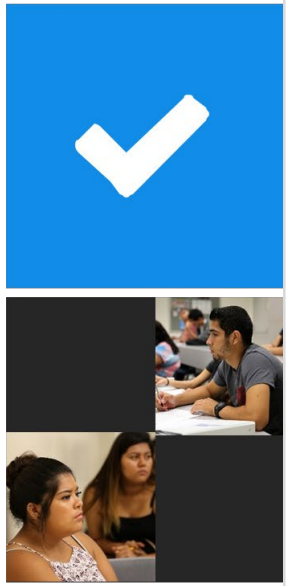
4-Week CFS Course Sequencing

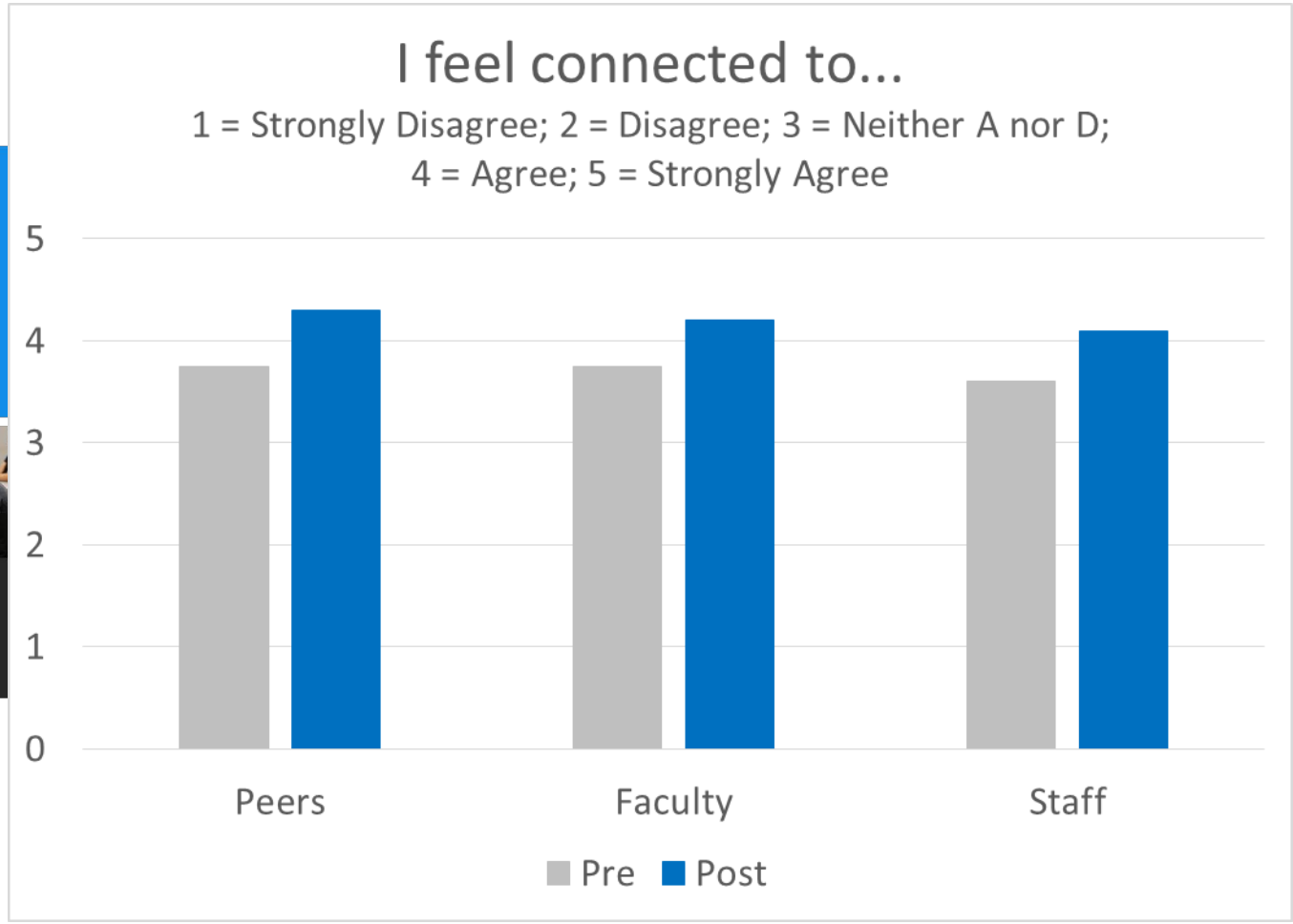


Summer Course Outcomes

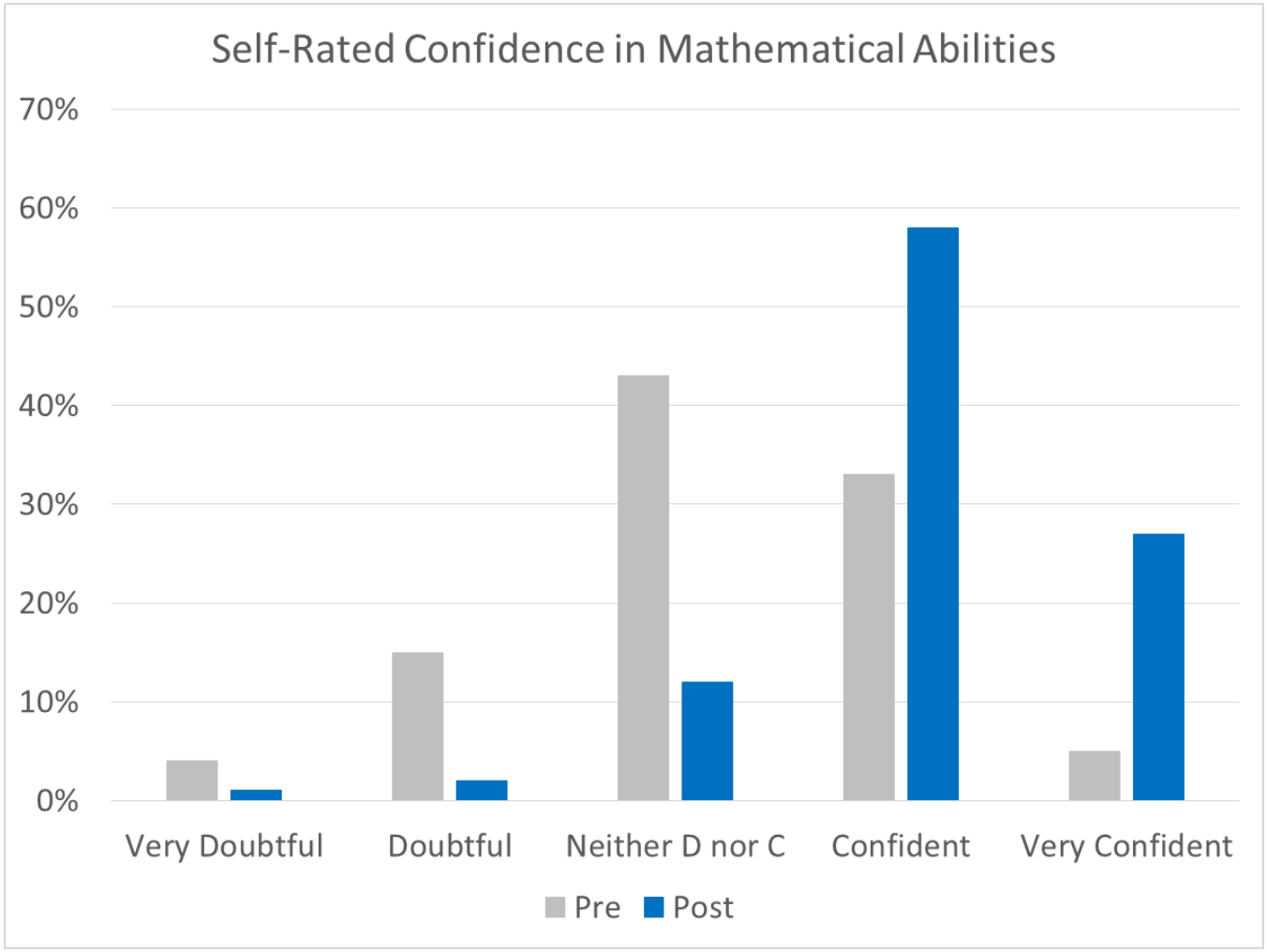
CFS Course	Count	Pass	Did Not Pass	% Pass
ESM 75A	68	61	7	90%
ESM 75B	375	343	32	91%
ESM 81	1217	1181	36	97%
ESM 91	1120	999	121	89%
Total	2780	2584	196	93%

Campus Connectedness



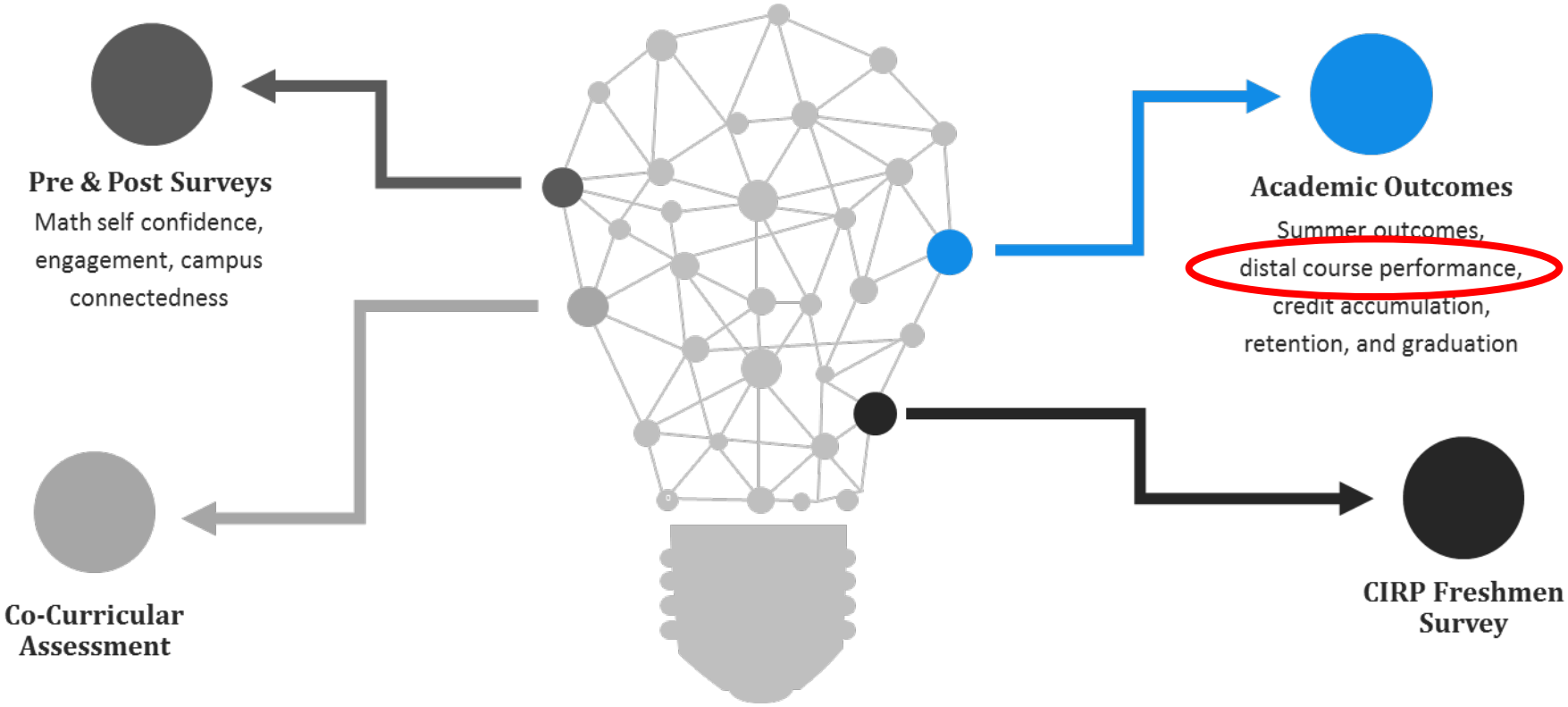


Math Self-Efficacy



Great work, IR!

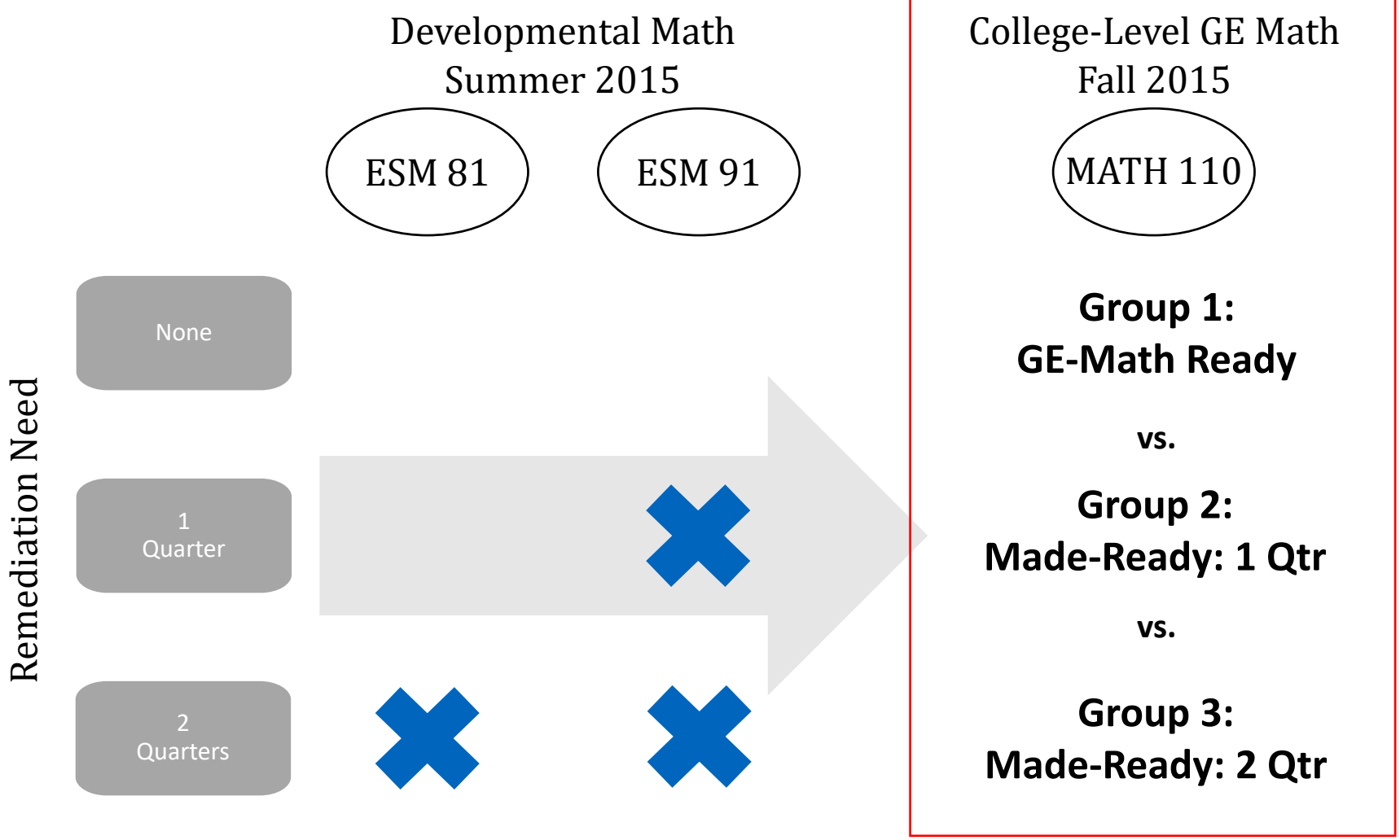
IR's Comprehensive Evaluation Plan



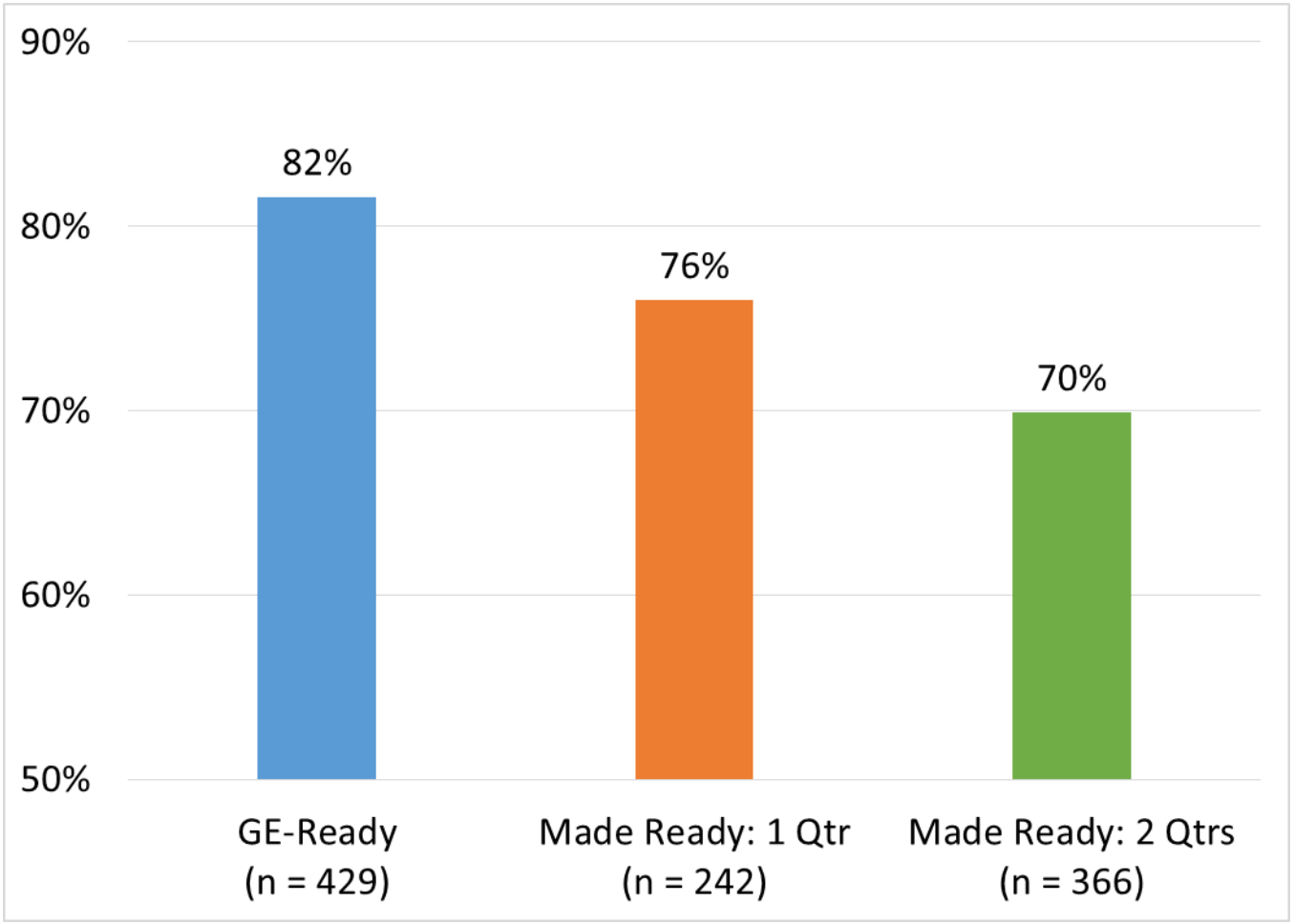
Visit the CSUSB IR website for updated CFS results:

https://www.csusb.edu/institutional-research

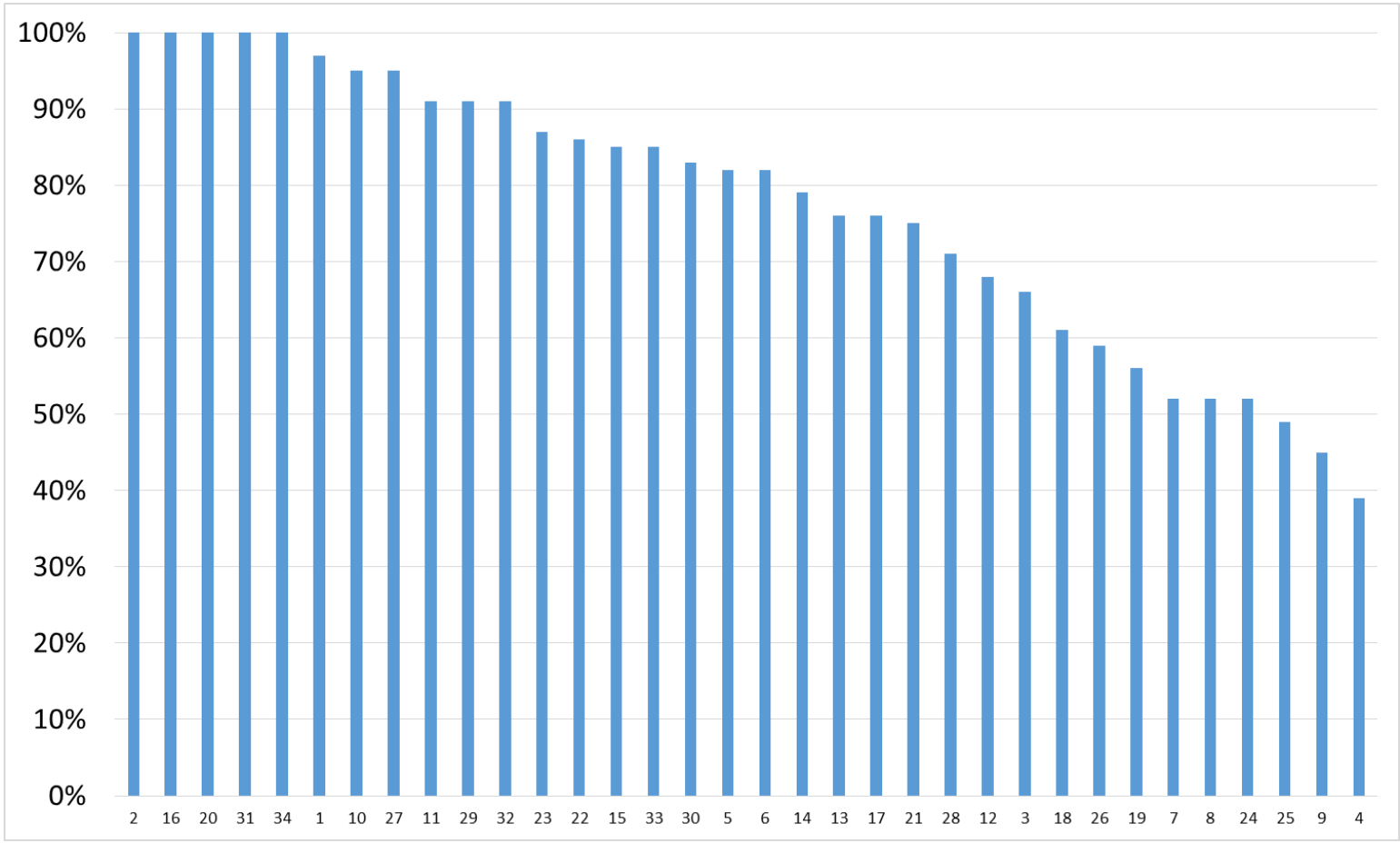
Distal Math Outcomes



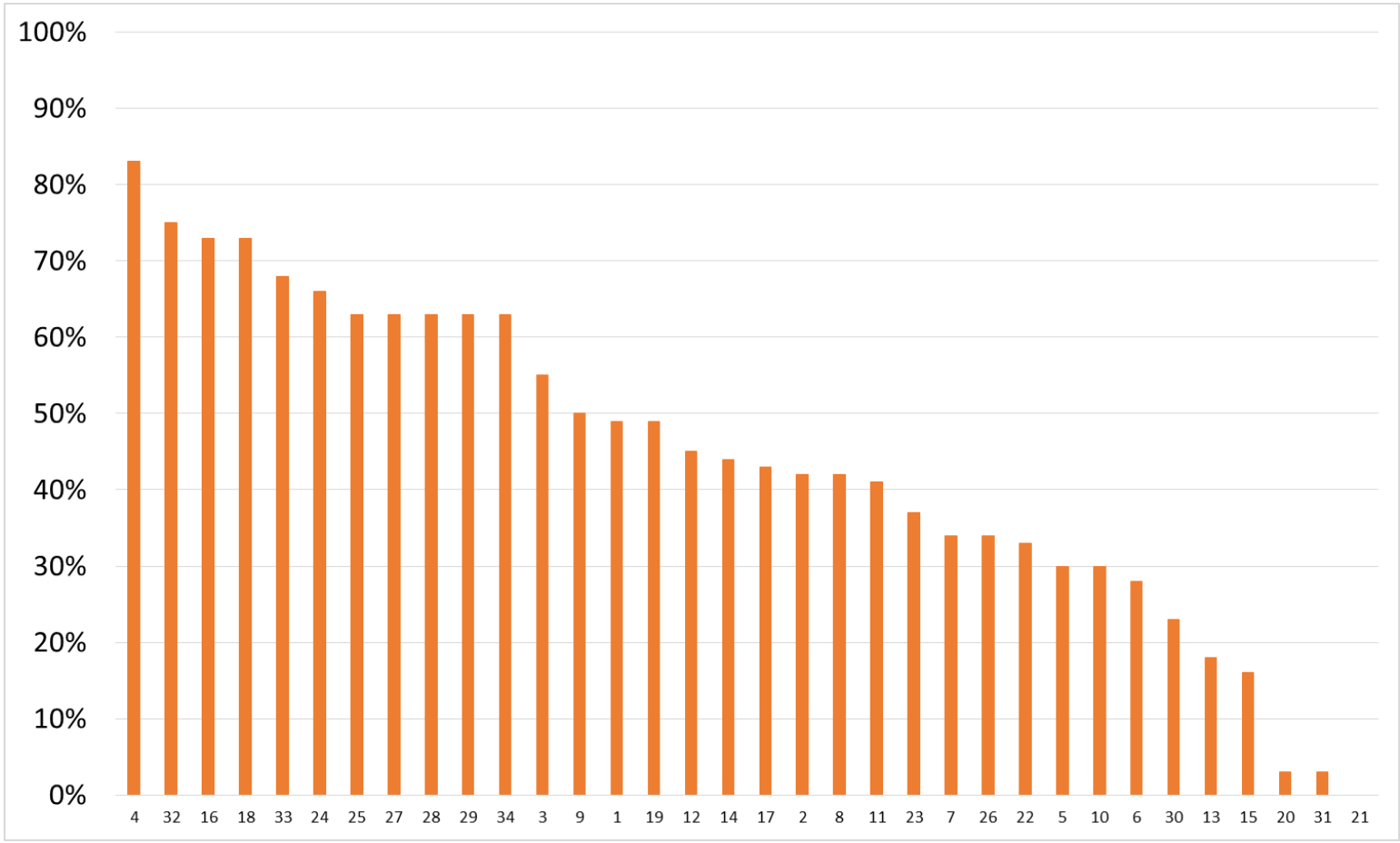
Math 110 Pass Rates



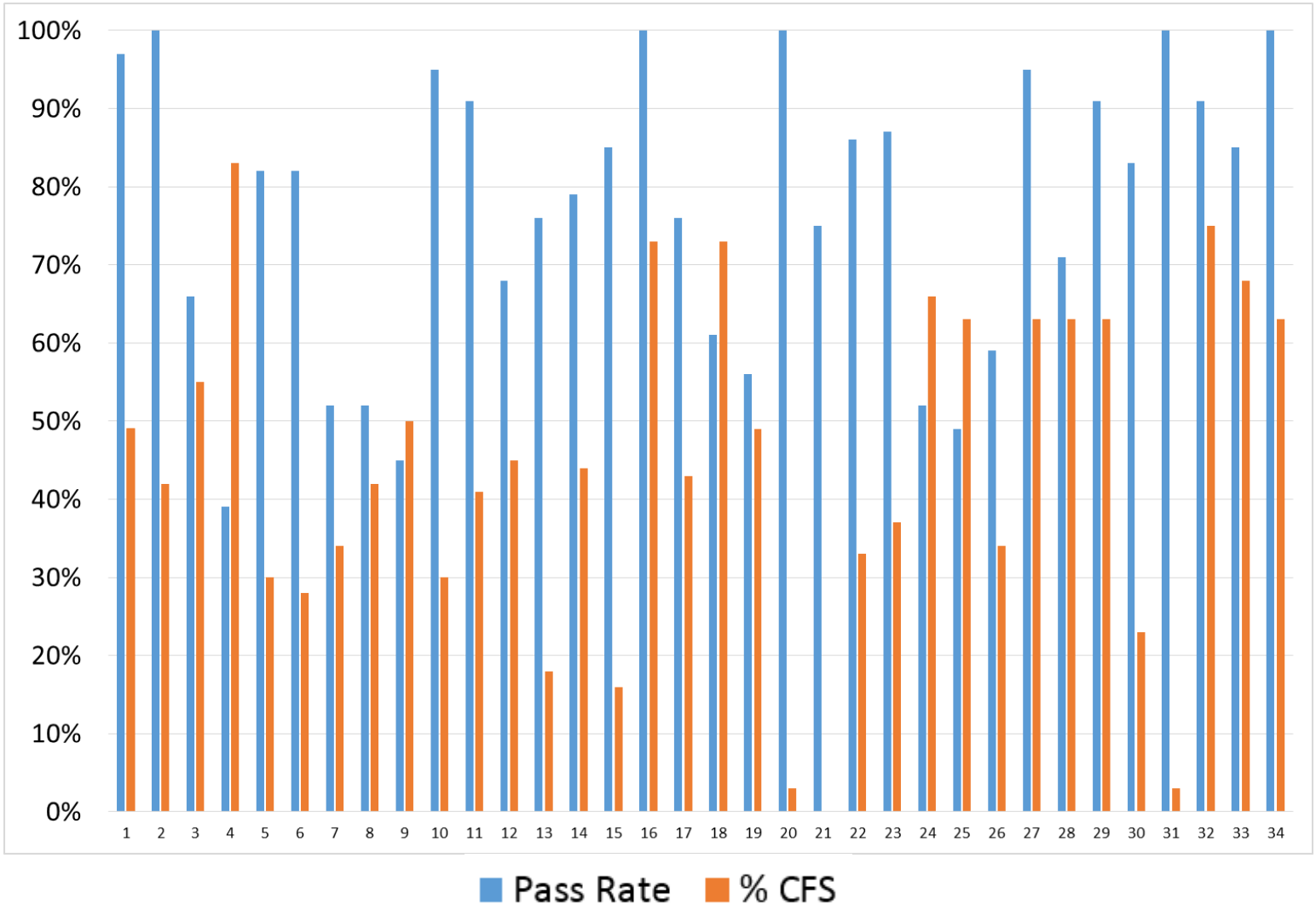
Math 110 Pass Rates by Section



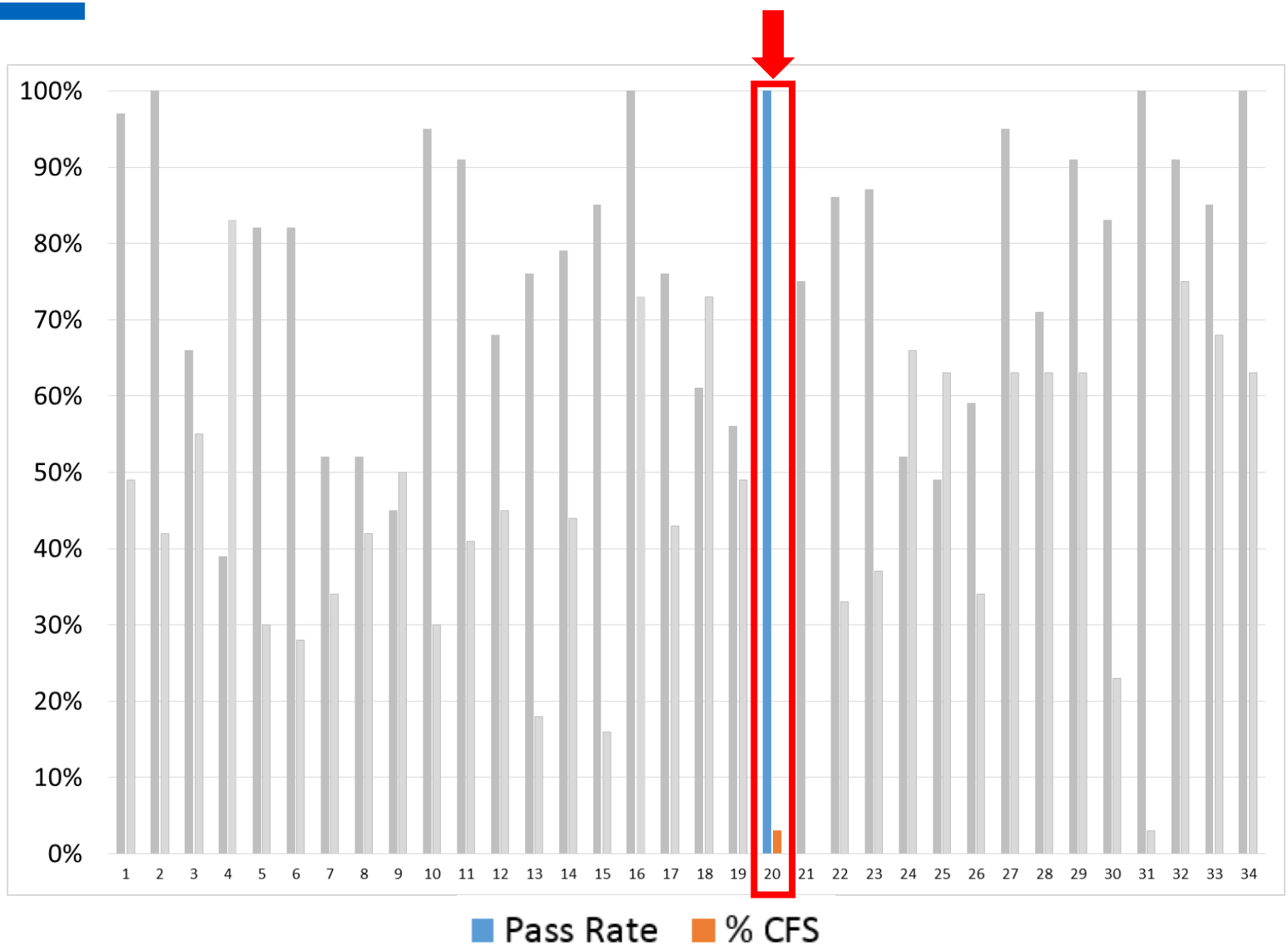
Sections by CFS Enrollment %



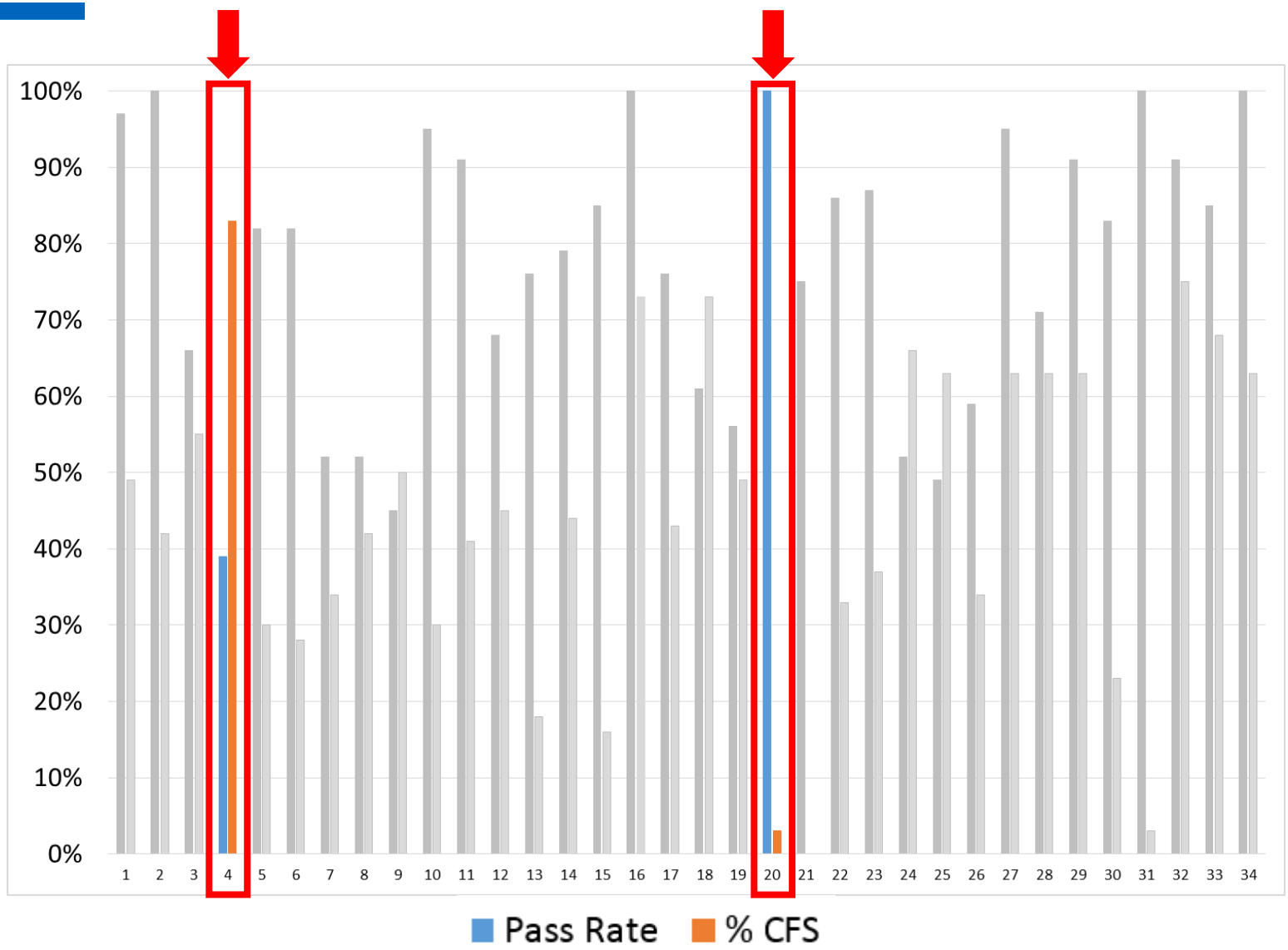
Math 110 Variability



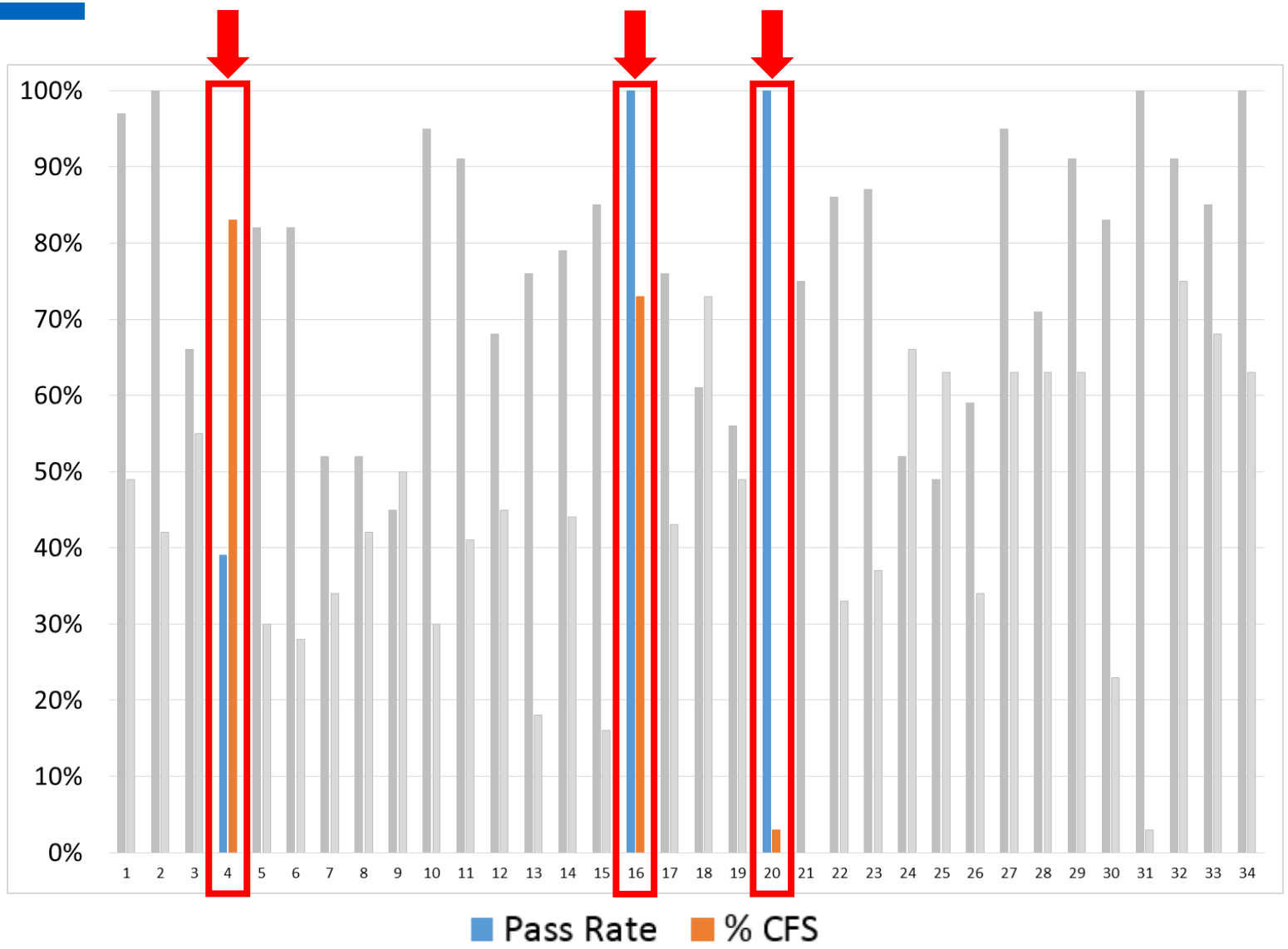
Math 110 Variability by Section



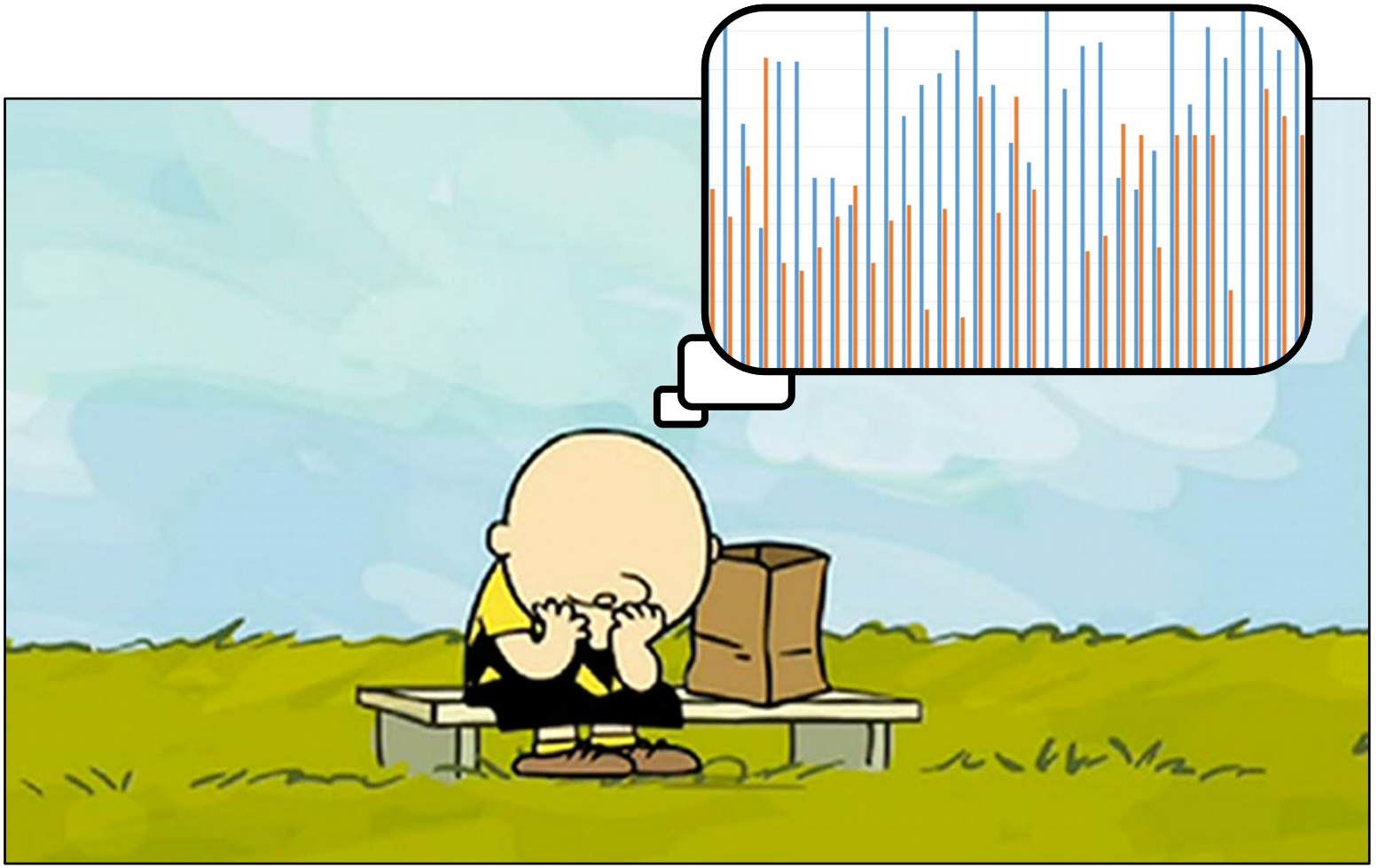
Math 110 Variability by Section



Math 110 Variability by Section



What the heck do we do now?



Multilevel Modeling

- Also known as hierarchical linear models (HLM), mixed models, and random effects models
- These statistical models are used when data are *nested*
  - Nested data exist when individuals are grouped in some way, usually naturally rather than experimentally
  - Examples: Students within sections, students within academic units, students within universities

So who cares if data are nested?

- Multilevel models are useful when data are nested to address:
  - *Violation of independence assumption*: Nested data violates this assumption of parametric linear statistical models
  - *Unit of analysis problem*: Hierarchical data structures have more than one unit of analysis
  - *Aggregation bias*: Incorrect inferences about individuals from group data
- Multilevel models take care of these issues

Study Overview

- *Purpose*: To examine the long-term effectiveness of Coyote First STEP by studying the relationship between pre-summer remediation status and college-level math outcomes
- *Subjects*: Fall 2015 FTF who attempted Math 110 in their first quarter at CSUSB
- *Statistical Software*: Mplus

Research Questions

- 1. Did Math 110 pass rates significantly differ between CFS and non-CFS students?
  - Do student background characteristics explain differences in pass rates?
  - Do section characteristics explain the differences in pass rates?
- 2. Did Math 110 pass rates significantly differ for CFS students across sections?

Table 1

Descriptive Statistics of Study Variables

Variable	Mean	Min	Max	SD
Outcome Variable				
Passed Math 110 in Fall 2015	.76			
Student-Level Variables (N = 1037)				
Pre-summer math remediation status				
No Remediation (reference, n = 608)	.41			
1 Quarter Remediation Need (n = 242)	.24			
2 Quarter Remediation Need (n = 366)	.35			

(continued)

Table 1 (continued)

Descriptive Statistics of Study Variables

Variable	Mean	Min	Max	SD
Student-Level Variables (cont.)				
Academic/demographic background covariates				
High school GPA (weighted)	3.20	2.21	4.29	.34
HS college-prep courses (semesters)	38.85	30.00	50.00	3.73
Male (reference)	.40			
Female	.60			
Non-URM (reference)	.23			
Underrepresented minority (URM)	.77			
< 15 enrolled units (reference)	.61			
≥ 15 enrolled units	.39			
Non first-generation (reference)	.43			
First-generation (parents no college)	.57			
Non-Pell Grant recipient (reference)	.31			
Pell Grant recipient	.69			

(continued)

Table 1 (continued)

Descriptive Statistics of Study Variables

Variable	Mean	Min	Max	SD
Section-Level Variables (N = 34)				
CFS class proportion	.44	.00	.83	.22
Two class meetings/week (reference)	.62			
Three class meetings/week	.38			
Morning course (before 10 a.m.; ref.)	.21			
Mid-day course (10 a.m. to 2 p.m.)	.50			
Afternoon course (after 2 p.m.)	.29			
Male instructor (reference)	.44			
Female instructor	.56			
Non-URM instructor (reference)	.56			
URM instructor	.44			
Lecturer (reference)	.71			
Graduate-student instructor	.29			

RQ 1

Table 2

HGLM Multilevel Model Building Results for Odds of Passing Math 110

Variable	Unconditional Model	Student-Level Model	School-Level Model
Student-Level Variables			
Pre-summer math remediation status			
1 quarter remediation need	0.763		
2 quarter remediation need	0.478**		
Academic/demographic background covariates			
High school GPA			
HS college-prep courses			
Female			
URM			
≥ 15 enrolled units			
First-generation			
Pell Grant recipient			
Section-Level Variables			
Course section characteristics			
Three class meetings/week			
Mid-day course (10 a.m. to 2 p.m.)			
Afternoon course (after 2 p.m.)			
Female instructor			
URM instructor			
Graduate-student instructor			
CFS class proportion			
Variance Component			
Estimate	1.500**		

Note. Parameter estimates in odds ratio (*OR*); *$p < .05$. **$p < .01$.

RQ 1

Table 2

HGLM Multilevel Model Building Results for Odds of Passing Math 110

Variable	Unconditional Model	Student-Level Model	School-Level Model
Student-Level Variables			
Pre-summer math remediation status			
1 quarter remediation need	0.763	0.952	
2 quarter remediation need	0.478**	0.549**	
Academic/demographic background covariates			
High school GPA		10.196**	
HS college-prep courses		1.033	
Female		0.939	
URM		0.722	
≥ 15 enrolled units		1.522*	
First-generation		0.684*	
Pell Grant recipient		0.886	
Section-Level Variables			
Course section characteristics			
Three class meetings/week			
Mid-day course (10 a.m. to 2 p.m.)			
Afternoon course (after 2 p.m.)			
Female instructor			
URM instructor			
Graduate-student instructor			
CFS class proportion			
Variance Component			
Estimate	1.500**	1.847**	

Note. Parameter estimates in odds ratio (*OR*); *$p < .05$. **$p < .01$.

RQ 1

Table 2

HGLM Multilevel Model Building Results for Odds of Passing Math 110

Variable	Unconditional Model	Student-Level Model	School-Level Model
Student-Level Variables			
Pre-summer math remediation status			
1 quarter remediation need	0.763	0.952	0.974
2 quarter remediation need	0.478**	0.549**	0.553**
Academic/demographic background covariates			
High school GPA		10.196**	10.340**
HS college-prep courses		1.033	1.033
Female		0.939	0.947
URM		0.722	0.714
≥ 15 enrolled units		1.522*	1.528*
First-generation		0.684*	0.674*
Pell Grant recipient		0.886	0.888
Section-Level Variables			
Course section characteristics			
Three class meetings/week			1.921
Mid-day course (10 a.m. to 2 p.m.)			0.656
Afternoon course (after 2 p.m.)			0.397
Female instructor			0.487
URM instructor			1.853
Graduate-student instructor			1.837
CFS class proportion			0.589
Variance Component			
Estimate	1.500**	1.847**	1.208**

Note. Parameter estimates in odds ratio (*OR*); *$p < .05$. **$p < .01$.

RQ 2

- Did Math 110 pass rates significantly differ for CFS students across sections?
- No, pass rates did not significantly differ for CFS students across sections
  - *Variation non-sig. for Made Ready: 1 Qtr slope (μ_{1j}: p > .05) and Made Ready: 2 Qtr slope (μ_{2j}: p > .05)*
- Interpretation
  - Made Ready: 1 Qtr students passed Math 110 at a similar rate to GE Ready students across all sections
  - Made Ready: 2 Qtr students underperformed GE Ready students similarly across all sections

Key Findings

- Pass rates significantly varied across sections
  - Section-level variables all nonsignificant in explaining differences in pass rates:
    - Class meetings (two versus three)
    - Class time (a.m., mid-day, or p.m.)
    - Instructor gender (male vs. female)
    - Instructor ethnicity (URM vs. non-URM)
    - Instructor type (graduate student vs. lecturer)
    - CFS class proportion (peer effects)

Key Findings

- No significant difference in pass rates between GE Ready and Made Ready: 1 Quarter students
  - After statistically adjusting for differences in pass rates across sections
  - Non-significance was consistent across sections
  - HS GPA and ≥15 units ↑ odds of passing
  - 1st-Gen ↓ odds of passing
  - A-G courses, gender, URM, and Pell non-significant

Key Findings

- Significant difference in pass rates between GE Ready and Made Ready: 2 quarter students
  - After statistically adjusting for differences in pass rates across sections
  - This achievement gap was consistent across sections

Implications

- Consistency in grading between mathematics instructors is an issue that should be addressed
- Coyote First STEP will focus on moving students up only one course level in the summer
- Redesigning mathematics curriculum
  - (1) Applied math and less algebra
  - (2) Advising non-STEM majors to enroll in non-STEM General Ed math course

Contact Us

Multilevel modeling

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Coyote First STEP assessment

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Gregory Palardy, Ph.D., Associate Professor of Education, UC Riverside