

# Making the Invisible Visible: Advancing Quantitative Methods in Higher Education using Critical Race Theory and Intersectionality

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# Background

- UNM Interdisciplinary Research Team



- Paper forthcoming in *Race, Ethnicity and Education* (2017)
- For more information visit the Institute for the Study of “Race” and Social Justice at [race.unm.edu](http://race.unm.edu)

# Big Picture Questions

1. What patterns of educational inequalities remain invisible when we treat race, gender, and class as independent?

In other words, what patterns of inequalities are undetected when we examine six-year undergraduate graduation rates by race alone, gender alone, or class alone?

2. How do estimated achievement gaps change when we recognize that such characteristics are dependent on one another?

# Big Picture Questions

3. How is the simultaneity of race/structural racism, settler colonialism, gender relations/patriarchy and class/capitalism experienced differently by students according to their location in intersecting systems of power, privilege, oppression and resistance in a given context?

# Research Question

- What are race-gender-class achievement gaps in six-year graduation rates and developmental course taking at a major public university in the American southwest over the period 2000 -2015
  - Binder and Ganderton (2004) study on broad merit-based lottery scholarships
  - Many state funding formulas in the US assume PELL status is a proxy for racialized “achievement” gap—not assumed for gender gap
  - Race-gender-class gaps are invisible in current policy conversations
  - Research for social justice policy and practice (praxis-action and reflection)



# Findings and Argument

- We find surprising race-gender-class gaps that would ordinarily remain unseen in conventional race-only, gender-only, and class-only reporting on graduation rates and developmental class placement.
- Race, gender, and class are interdependent in the context of outcomes in higher education
- We argue that one modality of “QuantCrit” can be guided by leveraging the ontologies of Critical Race Theory and Intersectionality to make the “invisible visible” or shine a light on intracategorical (within group) and intercategorical (across group) intersecting inequalities in higher education outcomes.



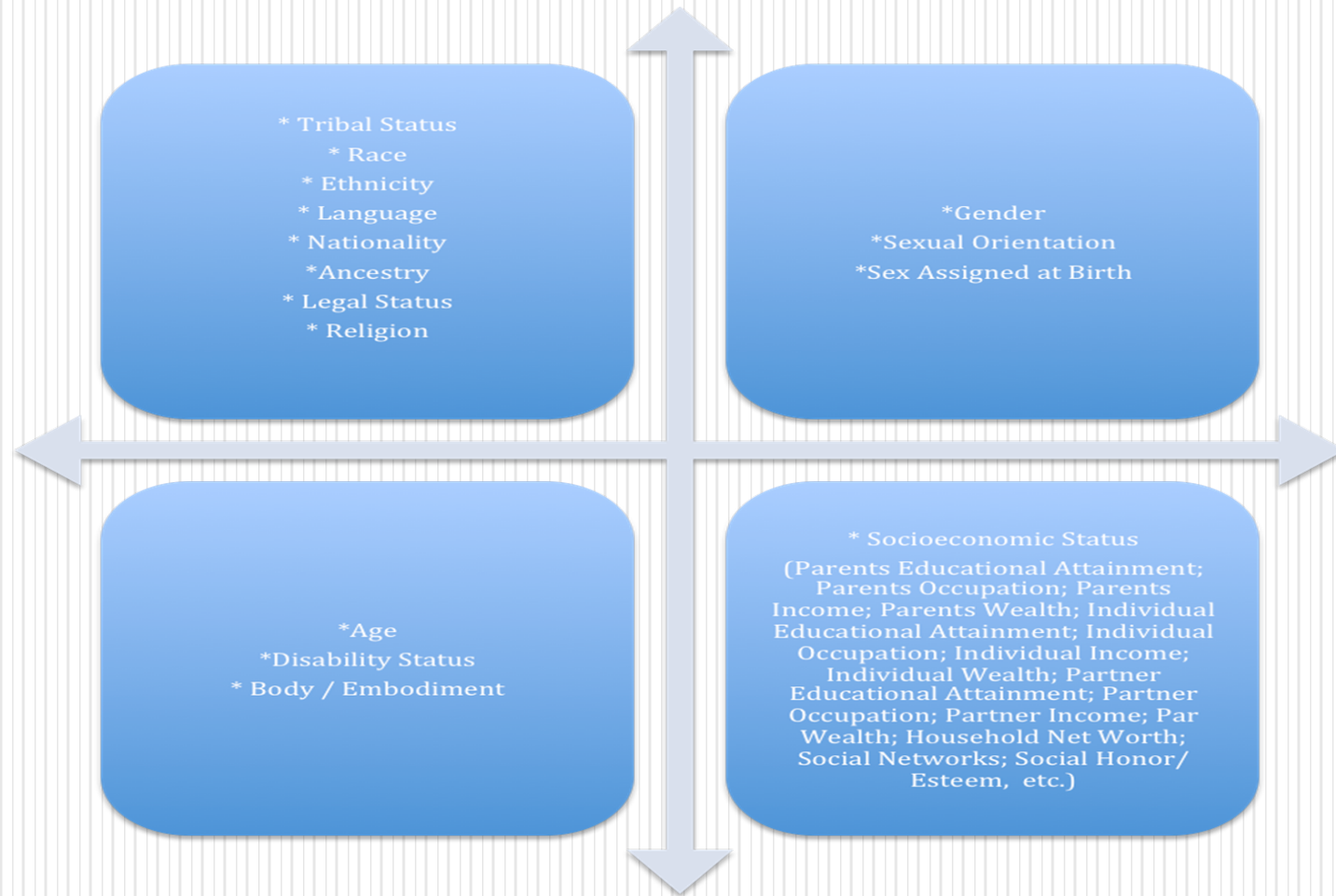
# An invitation to self-reflexivity...

- How can we take account of our social location within power relations?
- What is your lived race-gender-class lived experience?



Art by Augustine Romero  
([aztlancontemporary.com](http://aztlancontemporary.com))

# Conceptualizing and Visualizing Intersectionality



- Ongoing self-reflexivity about our own social location and category of experience in systems of power, privilege, and disadvantage



# Tenets of Critical Race Theory

1. Challenges the idea of neutrality in law (Brown and Jackson, 2013)
2. Liberal democracy and racism are inherently reinforcing (Ladson-Billings, 2013)
3. Racial realism-centrality and permanence of racism; Bell: most racial remedies remain symbolic (Ladson-Billings, 2013)
4. Interest convergence (Bell)
5. Counterstory/narratives and resistance (Yasso)



# “QuantCrit”: Opportunity for Conceptual Clarity and Transparency

- From Zuberi (2001):
  - “The conceptualization of race is fundamental to all subsequent use of racial data.”
  - “Studies should not rely on a decontextualized racial identity. It is, in fact, this decontextualization that has leads to racial reasoning.”



# Critical Race Theory (CRT) and Indigenous Statistics

- “CRT can be used to question the variables chosen (or ignored) in quantitative research as well as establish counter-narratives in qualitative research” (Brown & Jackson, 2013: 21)
- From Walter and Anderson (2013):
  - “Rather than representing neutral numerics, quantitative data play a powerful role in constituting reality through their underpinning methodologies by virtue of the social, cultural and racial terrain in which they are conceived, collected, analysed, and interpreted.”

# Critical Race Theory (CRT) and Indigenous Statistics

- More from Walter and Anderson (2013):
  - “...Indigenous quantitative methodologies can be construed as challenging colonizer settler quantitative practices.”
  - “An indigenous quantitative methodology is a quantitative methodology that embodies an Indigenous standpoint.”



# Intersectionality

- From Collins and Bilge (2016):
  - “Intersectionality is a way of understanding and analyzing complexity in the world, in people, and in human experiences. The events and conditions of social and political life and the self can seldom be understood as shaped by one factor. They are shaped by many factors in diverse and mutually influencing ways. When it comes to social inequality, people’s lives and the organization of power in a given society are better understood as being shaped not by a single axis of social division, be it race or gender or class, but by many axes that work together and influence each other. Intersectionality as an analytic tool gives people better access to the complexity of the world and of themselves.”



# Visual Matrix of Domination (Collins, 2009)

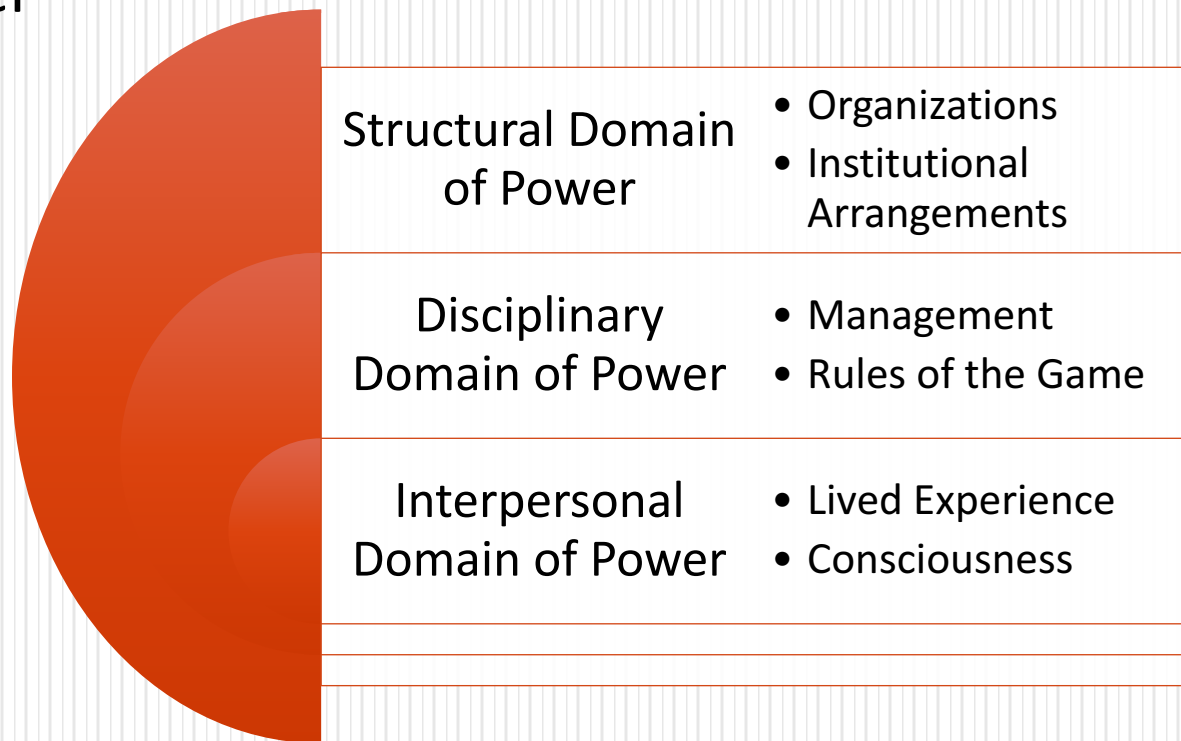
## 1. Intersecting systems of oppression

*colonization-patriarchy-sexism-structural racism-nativism-ableism*

## 2. Arrangements of power

Hegemonic/Cultural Domain of Power  
- Permeates all levels of Power

*(Ideological Glue that cuts across all domains)*



# Dynamic Centering: Radical Contextualized Relationality

- “Using dynamic centering for multiple social groups with diverse configurations of race, ethnicity; sexuality, class, age, gender, ability and citizenship status should expand sociology knowledge even further. Continuing this ongoing process of dynamic centering should, over time, yield a more complex and robust understanding of ... multiple sites of inequality whether, health, education, or law enforcement.” (Collins, 2007:594)



# Race-Gender-Class Social Locations Ontological Focus

- “Quantitative methodologies might be more successful if distinct composite variables were constructed to identify how the race, class and gender categories work in combination to form a different category of experience from that of any of the categories originally combined.”  
(Collins, 2007: 601)
- We analyze 20 social locations or unique “groups” in context in our models



# Radical Contextualization of a Southwestern State

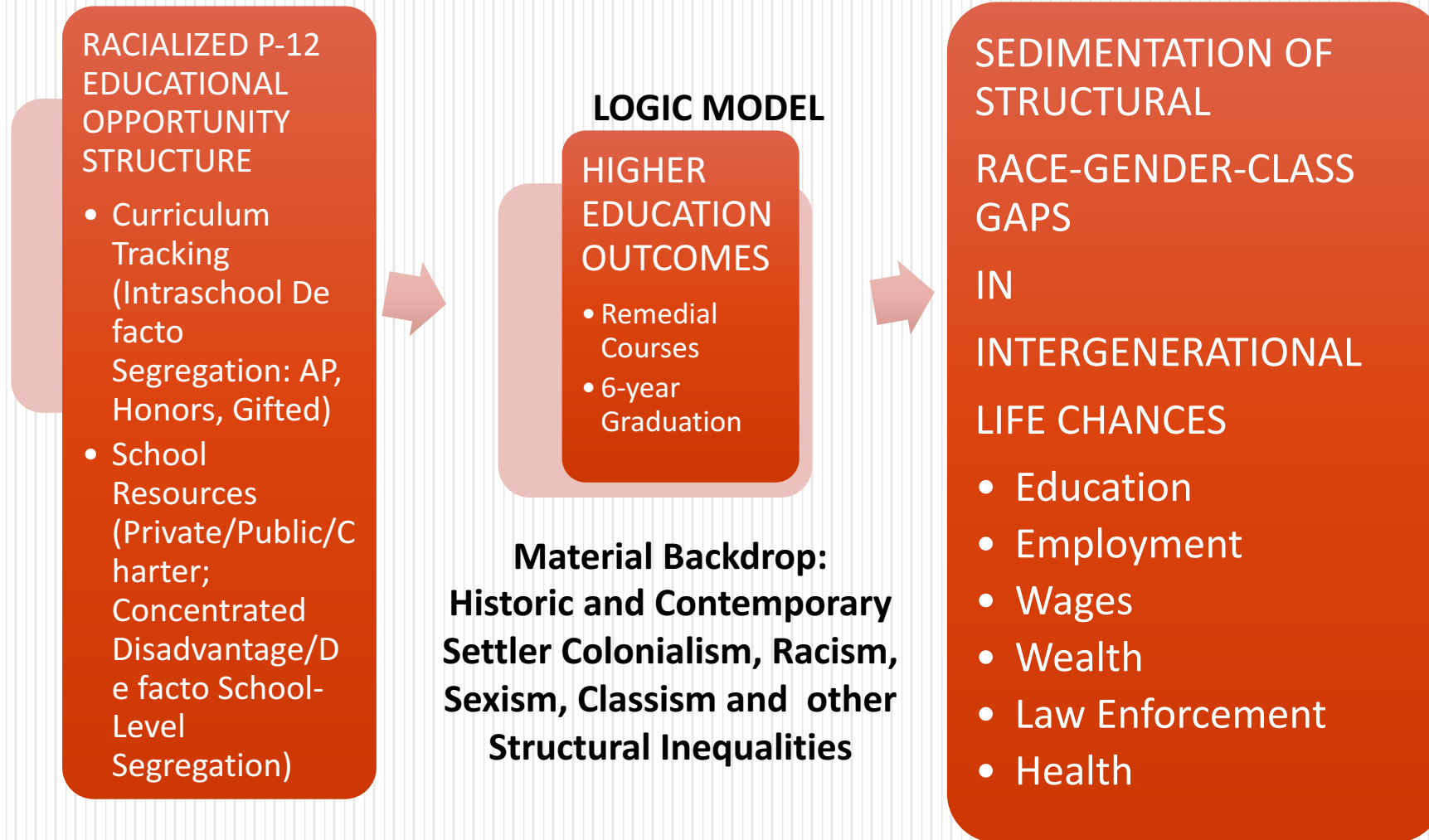
- Majority Minority State – A Case Study of Settler Colonialism (Gómez, 2007; Nakano-Glenn, 2015)
- Among the highest poverty rates for children in the country:
  - 59% of Native American
  - 25% of Hispanic
  - 20% of Black
  - 10% of White
- 4% of Whites living in the state have less than a high school education, compared to 24% of Hispanics



# Complex Intersecting Configurations of Inequalities: Race-Gender-Class

- “I find that there are in fact configurations of inequality, in which race, gender and class intersect in a variety of ways depending on underlying economic conditions in local economies...Indeed, configurations reveal that in local economies are all types of wage inequality systematically and simultaneously lower or higher; complex intersections of various dimensions of inequality are the norm....Policy and politics can play an important role in determining...which path is chosen and which forms of inequality are fostered or mitigated.” (McCall, 2001: 6)

# Radical Contextualization of Educational Opportunity Structure



# Racialized-Gendered Educational Opportunities

## Coloring and Gendering HS “Honors”: Feeder School District, 2009-2016

<u>Racial/Ethnic Origin</u>	<u>District (%)</u>	<u>Honors (%)</u>	<u>Gap (%)</u>
Hispanic	67	59	-8
White	21	29	8
Native American	4	2	-2
Black	2	2	0
Asian American	2	4	2
Multiracial*	3	3	0
*Gifted*	7	9	2
<u>Gender</u>	<u>Male (%)</u>	<u>Female (%)</u>	<u>Gap (%)</u>
	43	57	-7



# Racialized-Gendered Educational Opportunities

Coloring and Gendering HS “AP”: Feeder School District, 2009-2016

<u>Racial/Ethnic Origin</u>	<u>District (%)</u>	<u>AP (%)</u>	<u>Gap (%)</u>
Hispanic	67	61	-6
White	21	27	6
Native American	4	3	-1
Black	2	2	0
Asian American	2	4	2
Multiracial*	3	3	0
*Gifted*	7	6	-1
<u>Gender</u>	<u>Male (%)</u>	<u>Female (%)</u>	<u>Gap (%)</u>
	43	57	-7



# Racialized-Gendered Educational Opportunities

Coloring and Gendering HS “Giftedness”: Feeder School District, 2009-2016

<u>Racial/Ethnic Origin</u>	<u>District (%)</u>	<u>Gifted (%)</u>	<u>Gap (%)</u>
Hispanic	67	48	-19
White	21	40	19
Native American	4	2	-2
Black	2	1	-1
Asian American	2	4	2
Multiracial*	3	5	2
<u>Gender</u>	<u>Male (%)</u>	<u>Female (%)</u>	<u>Gap (%)</u>
	43	57	3



# Data

- Cross-sectional data on all full-time, first-time fall enrollees
- Data from 1980-2015
  - Graduation data from 2000 – 2008 (n = 6,427)
  - Developmental course taking data from 2000 – 2015 (n = 13,953)
- Socio-demographic information
  - Race, ethnicity, family income, gender
- High school information
  - Type and location, GPA, standardized test scores



# Data (Con't)

- College information
  - Developmental course taking, date of graduation
- Race and ethnicity mutually exclusive
  - 5 race-ethnicities, 2 genders, 2 class indicators
  - $5 \times 2 \times 2 = 20$  unique social locations
- Sample limited to in-state matriculants
- Sample limited to top and bottom income quartiles
- Missing many (~40%) self-reported family incomes from FAFSA



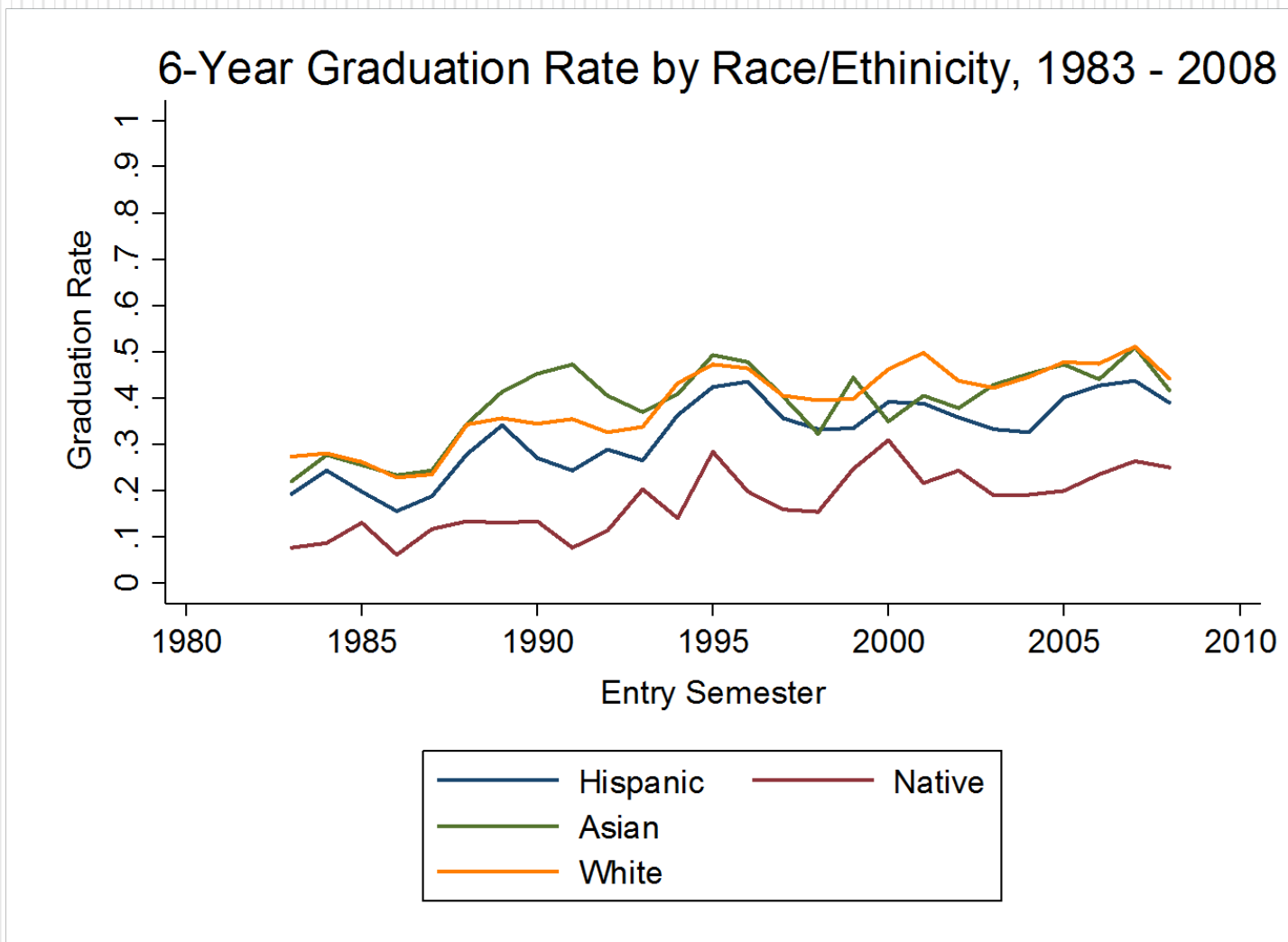


# Table 1. Descriptive Statistics

Variable	2000-2008	2000-2015
Graduated within 6 Years	.406	-
Remedial English	.294	.268
Remedial Mathematics	.326	.301
Any Remedial	.431	.397
Female	.582	.577
White	.406	.371
Black	.030	.024
Hispanic	.444	.499
American Indian	.069	.058
Asian	.050	.047
Low-Income	.539	.498
Observations	6,427	13,953

- In recent years the student body has: become less white, more Hispanic, less low-income, taken fewer remedial (developmental) courses.
- What has happened to graduation rates over time?

# Figure 1. Trends in Six-Year Graduation Rates



- The graduation achievement gap appears stable over time when just considering race-ethnicity
- Graphics such as these oversimplify the complex landscape of inequality in higher education

# Empirical Model

- Hierarchical linear models (students clustered within high schools)
  - AKA random intercept model
- Logistic regression
  - Saturated model with main effects and full set of interaction effects
- Outcomes are degree completion and developmental course placement
  - Graduation within 6 years
  - Mathematics and English developmental course taking



# Empirical Model

- Our focus is on dynamically centering students according to race, ethnicity, gender, and class
- Results are not causal
  - Achievement gaps are identified, but not explained causally
  - Many factors not included in the model are correlated with race, gender, and class as well as college success (e.g. family resources, parents' education, social attitudes, etc.)
    - Result: endogeneity problem



# Empirical Model

- Why saturated models can be powerful:
  - Example: naïve wage model using only gender and BA completion

$$wage_i = \beta_0 + \beta_1 Female_i + \beta_2 BA_i + \beta_3 Female_i \cdot BA_i + \varepsilon_i$$

- Main effects are  $\beta_1$  and  $\beta_2$ ; interaction effect is  $\beta_3$
- Summing main/interaction effects to calculate average wage for each group:
  - Men without degrees:  $\beta_0$
  - Men with degrees:  $\beta_0 + \beta_2$
  - Women without degrees:  $\beta_0 + \beta_1$
  - Women with degrees:  $\beta_0 + \beta_1 + \beta_2 + \beta_3$

# Empirical Model

$$(1) \quad y_{ij}^* = \alpha_0 + \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\gamma} + \mathbf{W}\boldsymbol{\delta} + \zeta_j + \varepsilon_{ij}$$

$$(2) \quad \zeta_j \sim N(0, \psi)$$

- $i$  denotes the student,  $j$  denotes the high school
- Errors,  $\varepsilon_{ij}$ , are assumed to have a standard logistic distribution with variance  $\phi$ .
- Model assumes that  $\zeta_j$  are independent across high schools and independent of main and interaction effects for student  $i$
- $\mathbf{X}$  is a vector of main effects
- $\mathbf{Z}$  is a vector of interaction effects
- $\mathbf{W}$  is a vector of cohort effects



# Empirical Model

- We estimate marginal effects and linear combinations of marginal effects with high-income, white women as the reference group
- Likelihood ratio test determine whether hierarchical model is an improvement over the standard logistic model (which ignores the natural clustering of students within high schools)
- We are particularly interested in intraclass correlation coefficients,  $\rho = \frac{\psi}{\psi + \phi}$ 
  - Large size would suggest that feeder high schools play a significant role in determining achievement gaps in higher education



# Results

- Six-year graduation rates
- Marginal effects
- Insightful, but difficult mental accounting
- Evidence that race, gender, and class are not independent

Variable	Marginal Effect		Standard Error
Black	-.226	***	.069
Hispanic	-.033		.026
American Indian	-.093	*	.055
Asian	.0009		.071
Low-Income	-.142	***	.026
Male	-.137	***	.025
Black x Low-Income	.183	**	.091
Hispanic x Low-Income	-.051		.036
American Indian x Low-Income	-.161	**	.074
Asian x Low-Income	.004		.085
Male x Low-Income	-.009		.040
Black x Male	.058		.144
Hispanic x Male	-.002		.039
American Indian x Male	-.140		.091
Asian x Male	-.075		.099
Black x Low-Income x Male	.050		.175
Hispanic x Low-Income x Male	.133	**	.056
American Indian x Low-Income x Male	.230	*	.123
Asian x Low-Income x Male	.141		.124
Likelihood Ratio Statistic			48.39
Residual Intraclass Correlation			.026
Observations			6,427





# Results

- Six-year graduation rates
- Linear combinations
- Easy to interpret
- Reveals complexity of inequality landscape

Variable	Marginal Effect		Standard Error	Cell Size
White, High-Income Women (Base)	-	-	-	869
White, Low-Income Women	-.142	***	.026	594
White, High-Income Men	-.137	***	.025	705
White, Low-Income Men	-.288	***	.031	440
Black, High-Income Women	-.226	***	.069	57
Black, Low-Income Women	-.185	***	.059	76
Black, High-Income Men	-.305	**	.126	18
Black, Low-Income Men	-.223	***	.077	45
Hispanic, High-Income Women	-.033		.026	599
Hispanic, Low-Income Women	-.225	***	.024	1,094
Hispanic, High-Income Men	-.172	***	.029	462
Hispanic, Low-Income Men	-.240	***	.027	699
American Indian, High-Income Women	-.093	*	.055	85
American Indian, Low-Income Women	-.396	***	.050	186
American Indian, High-Income Men	-.371	***	.072	66
American Indian, Low-Income Men	-.453	***	.066	108
Asian, High-Income Women	.0009		.071	50
Asian, Low-Income Women	-.137	***	.046	128
Asian, High-Income Men	-.211	***	.069	54
Asian, Low-Income Men	-.217	***	.055	92
Likelihood Ratio Statistic				48.23
Residual Intraclass Correlation				.025
Observations				6,427



# Results

- Developmental English placement
- Marginal effects
- Non-white and low-income groups more likely to take such courses

Variable	Marginal Effect		Standard Error
Black	.188	***	.047
Hispanic	.142	***	.019
American Indian	.152	***	.041
Asian	.129	***	.049
Low-Income	.085	***	.022
Male	.032		.021
Black x Low-Income	.017		.061
Hispanic x Low-Income	.065	**	.026
American Indian x Low-Income	.163	***	.049
Asian x Low-Income	.129	**	.057
Male x Low-Income	.015		.031
Black x Male	.020		.081
Hispanic x Male	.004		.027
American Indian x Male	.074		.056
Asian x Male	-.075		.072
Black x Low-Income x Male	-.062		.102
Hispanic x Low-Income x Male	-.031		.038
American Indian x Low-Income x Male	-.179	**	.070
Asian x Low-Income x Male	.039		.085
Likelihood Ratio Test Statistic			372.37
Residual Intraclass Correlation			.075
Observations			13,953



# Results

- Developmental English placement
- Linear combinations
- Nearly all groups more likely to take course relative to base group

Variable	Marginal Effect		Standard Error	Cell Size
White, High-Income Women (Base)	-	-	-	1,843
White, Low-Income Women	.085	***	.022	1,043
White, High-Income Men	.032		.021	1,578
White, Low-Income Men	.133	***	.023	718
Black, High-Income Women	.188	***	.047	97
Black, Low-Income Women	.291	***	.040	118
Black, High-Income Men	.240	***	.066	45
Black, Low-Income Men	.295	***	.048	75
Hispanic, High-Income Women	.142	***	.019	1,665
Hispanic, Low-Income Women	.292	***	.018	2,455
Hispanic, High-Income Men	.178	***	.020	1,260
Hispanic, Low-Income Men	.312	***	.019	1,588
American Indian, High-Income Women	.152	***	.041	153
American Indian, Low-Income Women	.400	***	.029	331
American Indian, High-Income Men	.258	***	.040	126
American Indian, Low-Income Men	.342	***	.033	203
Asian, High-Income Women	.129	***	.049	118
Asian, Low-Income Women	.343	***	.031	233
Asian, High-Income Men	.086		.053	117
Asian, Low-Income Men	.354	***	.033	187
Likelihood Ratio Test Statistic				372.37
Residual Intraclass Correlation				.075
Observations				13,953



# Results

- Developmental mathematics placement
- Marginal effects
- Mostly main effects significant
- Men less likely to take courses; Asian and white students similar

Variable	Marginal Effect		Standard Error
Black	.231	***	.049
Hispanic	.176	***	.019
American Indian	.134	***	.042
Asian	-.027		.059
Low-Income	.157	***	.020
Male	-.103	***	.022
Black x Low-Income	-.025		.065
Hispanic x Low-Income	-.028		.025
American Indian x Low-Income	.053		.052
Asian x Low-Income	.014		.069
Male x Low-Income	-.062	*	.034
Black x Male	-.005		.092
Hispanic x Male	-.011		.029
American Indian x Male	-.013		.067
Asian x Male	-.029		.097
Black x Low-Income x Male	.127		.116
Hispanic x Low-Income x Male	.027		.042
American Indian x Low-Income x Male	.006		.083
Asian x Low-Income x Male	.025		.114
Likelihood Ratio Test Statistic			407.11
Residual Intraclass Correlation			.081
Observations			13,953



# Results

- Developmental mathematics placement
- Linear combinations
- Low-income women have higher likelihoods of being placed in these courses

Variable	Marginal Effect		Standard Error	Cell Size
White, High-Income Women (Base)	-	-	-	1,843
White, Low-Income Women	.157	***	.020	1,043
White, High-Income Men	-.103	***	.022	1,578
White, Low-Income Men	-.008		.026	718
Black, High-Income Women	.231	***	.049	97
Black, Low-Income Women	.363	***	.044	118
Black, High-Income Men	.123		.078	45
Black, Low-Income Men	.320	***	.054	75
Hispanic, High-Income Women	.176	***	.019	1,665
Hispanic, Low-Income Women	.305	***	.018	2,455
Hispanic, High-Income Men	.061	***	.021	1,260
Hispanic, Low-Income Men	.155	***	.019	1,588
American Indian, High-Income Women	.134	***	.042	153
American Indian, Low-Income Women	.345	***	.031	331
American Indian, High-Income Men	.018		.053	126
American Indian, Low-Income Men	.172	***	.037	203
Asian, High-Income Women	-.027		.059	118
Asian, Low-Income Women	.145	***	.036	233
Asian, High-Income Men	-.159	**	.077	117
Asian, Low-Income Men	-.025		.046	187
Likelihood Ratio Test Statistic				372.37
Residual Intraclass Correlation				.075
Observations				13,953



# Selection Bias

- Income gathered from the FAFSA, but only 42% of students filed
- FAFSA filers and non-filers likely different in several ways (esp. in terms of income)

Variable	Present	Missing	Diff.
Graduation within 6 Years	.406	.435	-.028***
Remedial English	.294	.229	.065***
Remedial Mathematics	.326	.269	.057***
Any Remedial	.431	.362	.069***
Female	.582	.533	.049***
White	.406	.578	-.172***
Black	.030	.018	.013***
Hispanic	.444	.344	.100***
American Indian	.069	.023	.047***
Asian	.050	.038	.012***
Observations	6,427	8,930	

# Selection Bias

- Men much less likely to file FAFSAs
- White students least likely group to file the FAFSA

Group	Proportion Missing	Cell Size
White Women	.648	4,154
White Men	.683	3,614
Black Women	.409	225
Black Men	.508	128
Hispanic Women	.502	3,400
Hispanic Men	.541	2,527
American Indian Women	.279	376
American Indian Men	.356	270
Asian Women	.475	339
Asian Men	.549	324
Overall	.582	15,357

# Selection Bias

- Overall, descriptive evidence suggests that students that do not file a FAFSA may be of more privileged social locations (e.g., white, male, etc.) and also may have sufficiently high income to not qualify for the Federal PELL Grant Program.
- Inclusion of these students, which arguably have a greater chance of succeeding in college, would likely only widen the achievement gaps we estimate in our model
- For this reason, we believe our estimates are biased downwards (i.e., conservative achievement gaps)





# Limitations

1. Only includes first-time, full-time in-state students (i.e., no transfers or out of state students)
2. Family income not readily available for all students
3. Wish list: multidimensional class or SES student characteristics, LGBTQ and gender
4. Hispanic origin data does not allow for disaggregation by experiences by race, nativity, generational status
5. African American and Asian data are small; reflective of the school and state demographics



# Conclusions

- Graduation findings:
  - Main effects: black students (23% less) and American Indian students (10% less) far less likely to graduate than their white counterparts
  - More main effects: Men approx. 14% less likely to graduate than women; low-income students approx. 14% less likely to graduate compared to high-income students
  - Interaction effects: being non-white, coming from a poor family, and being male tend to interact to produce additional penalties in terms of graduation likelihood

# Conclusions

- Developmental course taking findings:
  - English courses: more likely for non-white students (13-19%) and for students from low-income families (9%); men are no more likely to take such courses than women. Being non-white and coming from a poor family tends to result in further increases in the likelihood of being placed in such courses.
  - Mathematics courses: Remedial mathematics course taking is more common for non-white (but not Asian) students, and less likely for men. Low-income men were less likely to be placed in remedial mathematics.



# Conclusions

- Assuming independence of race, gender, and class oversimplifies the complex nature of achievement gaps in higher education
  - Statistical significance of interaction effects is evidence of interdependence
  - Statistical significance of main effects reveals they also have their own measureable effects on success in college as well
- Our paper offers a new method of assessing the often complex nature of inequality along multiple interdependent individual-level characteristics



# Policy Implications

- Class is not a proxy for the familiar racial (and gender) achievement gap in six-year college graduation or remedial class placement
- Revisit policies that assume class is proxy for race (universal scholarship programs, funding formula, etc.)
- Targeting aid towards students from low-income families may not be enough if other characteristics generally stifle their ability to succeed in college



# Policy Implications

- Embracing intersectional knowledge projects in all local, state, and federal reporting for equity—create a feasible data infrastructure for P-20 that includes measures of class (parental educational attainment, wealth) and other axes of inequality including Hispanic origin as separate from race (not analytically equivalent) and sexual orientation
- Revisit legislation that conflates class status with the racialized achievement gap



# Next Steps

- Get it in print!
- Use two nationally representative longitudinal studies (NELS:88 and ELS:2002) from the Department of Education to assess the external validity of our findings
- Employ the methodology in other fields, such as labor market outcomes, criminology, health, etc.



# Thank You!

- Feel free to contact the authors:
  - Nancy López: [nlopez@unm.edu](mailto:nlopez@unm.edu)
  - Christopher Erwin: [cpe@unm.edu](mailto:cpe@unm.edu)
- Invitations:
  - Census mini-Symposium, U of Maryland-College Park, 11/9/17 8-1:30pm
  - Critical Race Studies in Education Association, 5/30/18-6/1/18 at UNM
    - Call for papers mid-August: [crsea.org](http://crsea.org)
- Questions?

