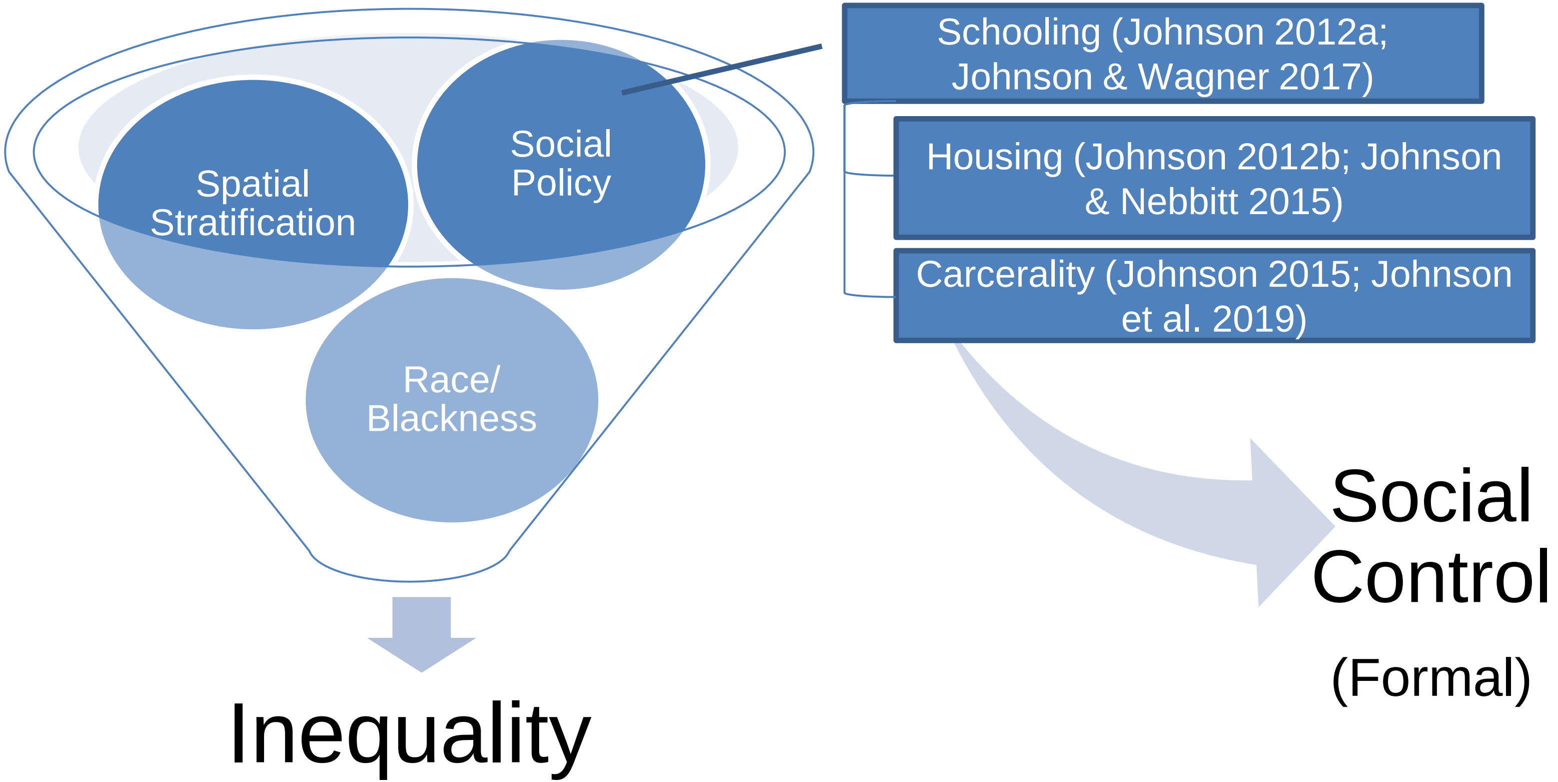
Will Draining the School-to-Prison Pipeline Help Fill the STEM Pipeline?

Odis Johnson Jr., PhD
Director, Institute in Critical Quantitative, Computational, & Mixed Methodologies (ICQCM)
Associate Director, Center for The Study of Race, Ethnicity & Equity (CRE2)
Professor, Departments of Sociology & Education
Faculty Scholar, Institute for Public Health

Washington University in St. Louis

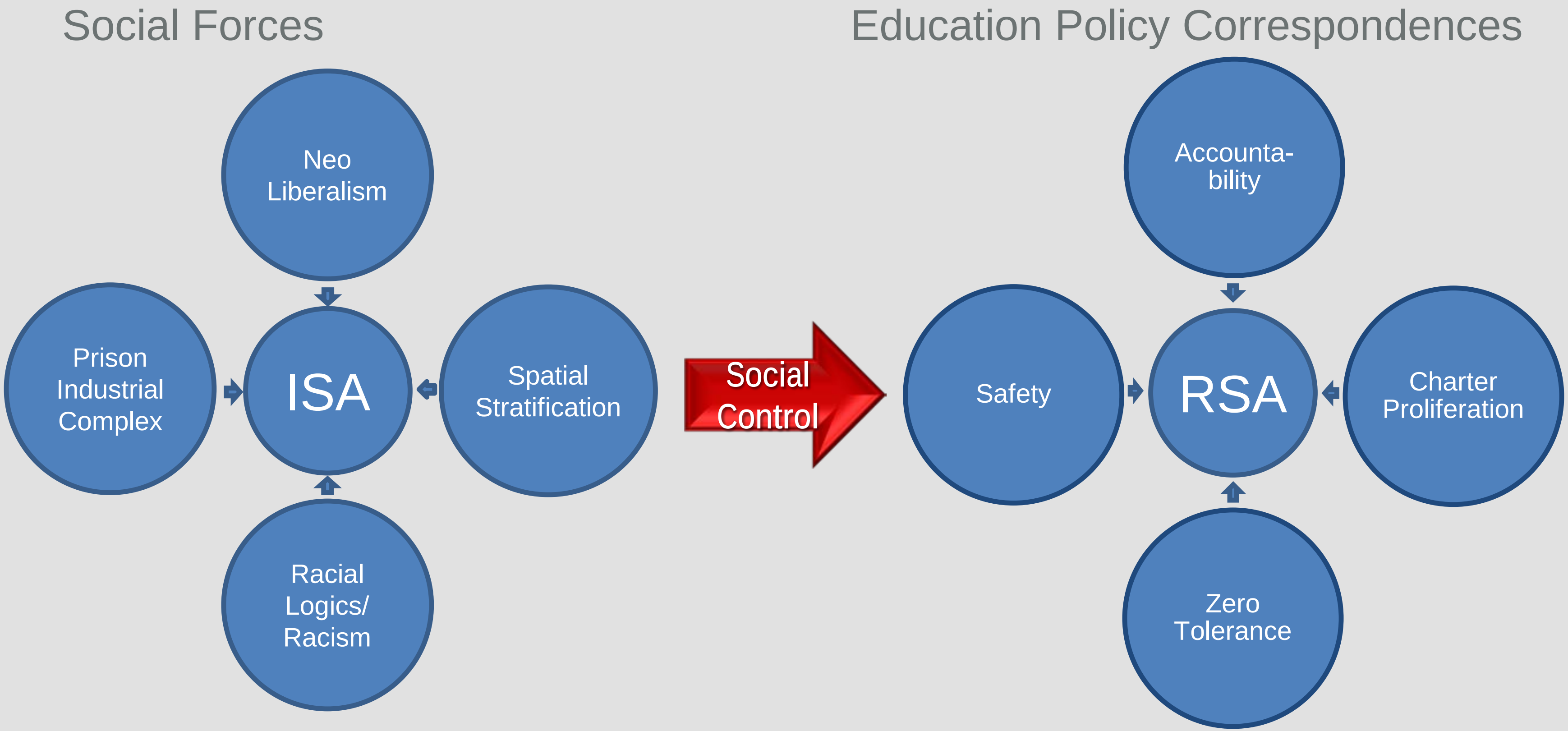
Research Perspective



What is Social Control?

- Informal Social Control
  - Maintenance of social order through the adherence to and internalization of shared norms (Durkheim 1961), i.e. “internal group regulation” (Kirk 2009)
  - “A repressive moral code that preserves public order” (Massey 1996).
- Formal Social Control
  - The “State” and “state apparatuses” (Althusser 1969; Foucault 2009)
  - “Institutional regulation of life” (Lacombe 1996), i.e. the laws, government action and institutions that arise in reaction to perceived deviance (Parsons 1937)
- Repression/Coercion
  - “Any social order, including a society with a relatively effective system of social control, will require an element of coercion” (Janowitz 1975).
  - “Social control technologies” (Foucault 1975)

School Transformation?

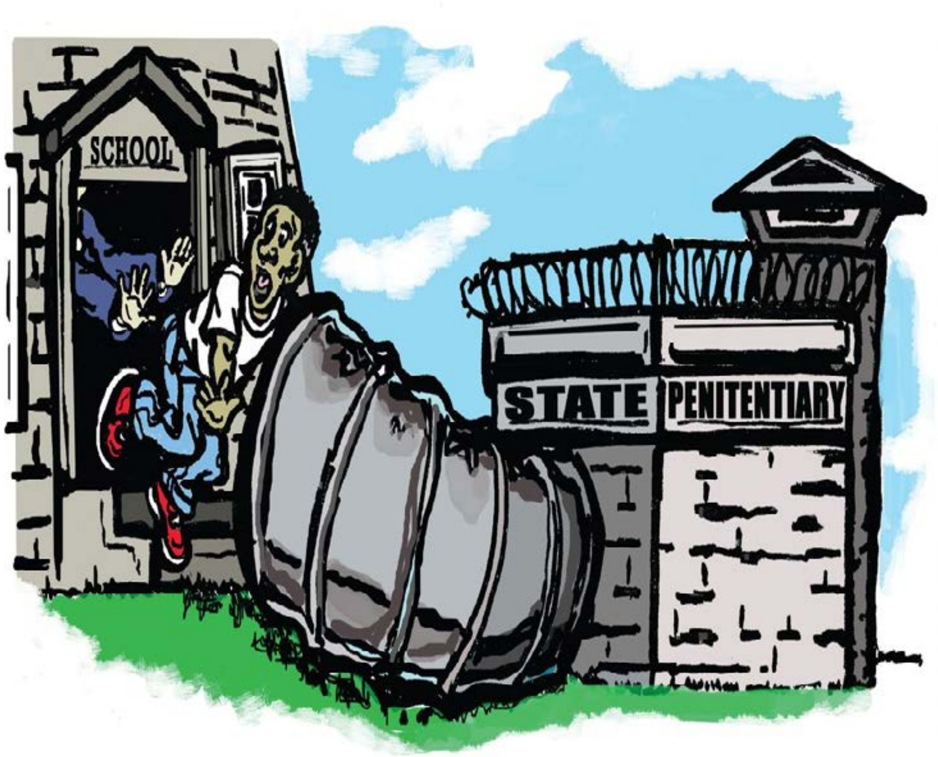


Evidence

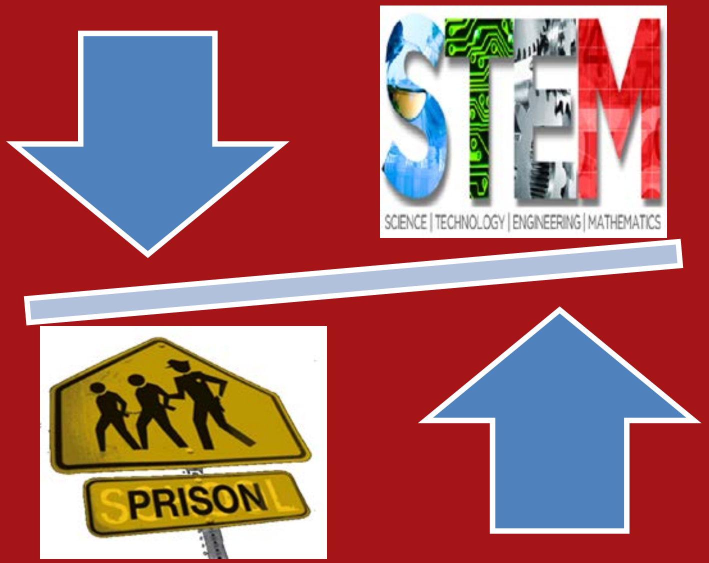
- Yearly high school suspension and expulsion rate up roughly 40% (Losen and Martinez 2013)
- SRO usage rose 16% (Losen et al., 2015)
- From 2005 to 2014, police in San Bernardino arrested 6,923 minors on streets but ~30,000 in schools (Ferriss 2015)

- School victimization rates (Butts 2000)
- School homicides (Robers et al. 2014)
- Teacher reports of threats (Fox and Burstein 2010)

School to Prison Pipeline and Race



- U.S. Black suspension rate in K-12 rose from 6% in 1973 to 16% by 2012 (Losen et al. 2015), and again in 2015-2016 to 25% and 14% for Black males and Black females, respectively (Blad and Mitchell 2018).
- Black students made up 15% of all public school students in 2015-16 but 31% of those arrested or referred to police—up by 5 percentage points since 2013-14 (U.S. Dept. of Education 2015).
- Federal data show the national suspension rate of Hispanic males trails that of Black males but exceeds that of both Black and Hispanic females (Ibrahim and Johnson 2018).



Will Draining the School to Prison Pipeline help Fill the STEM Pipeline?

Washington University in St. Louis

Central Hypothesis

The order, conformity, and obedience seeking school strategies (i.e. social control) to which certain race-gender groups are disproportionately exposed, are related to lowered levels of the qualities that are known to support success in STEM, including collaborative problem solving and interpersonal confidence; engagement and self-efficacy; and creativity.

Improving Federal Data for Social Control Research

NSF-EEC #1619843 ($617,202), “Race-Gender Trajectories in Engineering: The Role of Social Control across Neighborhood and School Contexts.”

NSF-EHR #1800199 ($299,990), “Assessing Social Control in Charter and Traditional Schools via Merged Data to Broaden the Participation of Race-Gender Groups in STEM.”

NSF-EEC # 1833161 ($99,985), “Race-Gender Trajectories in Engineering: The Role of Social Control across Neighborhood and School Contexts” (Supplement).

NSF-EHR #1800199: Involves linking several NCES datasets to explore questions that currently cannot be investigated through a singular data structure, including:

- The High School Longitudinal Survey (HSLS09)
- School Survey on Crime and Safety (SSOCS)
- Fast Response Survey System (#106) School Safety and Discipline Survey
- Common Core of Data (CCD)

THEORIZING THE MECHANISMS

“Collateral” Consequences (Perry and Morris 2014; Lacoe and Steinberg 2018; Peguero et al. 2018)

- Population-based spillover effects that lead to higher suspension rates (Jencks and Mayer 1990)

- Negative Vicarious Experiences/ Linked Fate (Brunson and Miller 2009; Kupchik 2010)

What Remains Unknown…

How widespread is the problem - a national concern?

How might the effects differ for ISS, a different form of exclusionary social control?

Do these effects persist within a causal framework that addresses the issue of non-random selection?

If they matter at all, how long do the effects of social control last?

We Advance Research by…

- Using school rates of ISS, a form of exclusionary social control, to classify schools as having relatively high or low levels of social control (counterfactual treatments).
- Using ISS because most existing research is about OSS, and because moratoriums on OSS may relate to higher levels of ISS
- Relating these two treatments to the math test-scores (immediate) and college attendance (distal) of a nationally representative sample of high school students.
- Developing propensity score weights to adjust for bias that extends from students' non-random selection into high and low suspension schools.

High School Longitudinal Study (HSLS) of 2009

- An average of 27 ninth-graders at each of the 944 schools were selected for a total of 25,206 eligible students (Ingels et al. 2011).
- This analysis utilizes student, parent, and administrator questionnaire data from the base year (fall of 9th grade), first follow-up (spring of 11th grade), the 2013 high school transcript study, and the second follow up.
- Missing values were imputed using MICE (“multiple imputation using chained equations”).

Methodology

- Counterfactual Modeling
  - An approach to derive causal inferences from seemingly observational data (Morgan and Winship 2007; Johnson and Wagner 2017).
  - Testing and juxtaposing both treatments (low and high social control schooling contexts) facilitates the **causal** inferences that we hope to make about social control's relationship to our outcomes.
- Propensity scores
  - Represent the predicted probability that individuals with *certain qualities* will experience a treatment when assignment to those conditions is essentially nonrandom (Guo and Fraser 2015)
  - IPTW "Inverse probability of treatment weights" estimator for ATE using GBM

Methodology

Creating the Treatment

- Used a student self-reported measure of ISS frequency (scaled 1 = “never suspended” to 5 = “suspended ten or more times” within the previous six months).
- Base-year student weight (W1STUDENT) was used to create a weighted mean of suspensions for each individual high school.
- Based on this measure, high schools were segmented into quintiles.
- The highest quintile (192 schools with 5,041 students) was operationalized as high-social control schools, while the lowest quintile (233 schools with 5,971 students) was operationalized as low-social control schools (1 = high-suspension school; 0 = low-suspension school).

Methodology

Propensity Score Weighting

7 Step Method

- A propensity score was estimated based on the observed covariates of a specific treatment using generalized boosted regression models (GBM)
- An inverse probability treatment weight was created based on the propensity score
- Propensity score weights were multiplied by the necessary survey weights
- Checks were completed to ensure observed covariates were properly balanced
- Checks were completed to ensure normally distributed and adequately overlapped scores
- Weighted analyses of the specified treatment were completed
- Sensitivity analysis was performed to ensure that unobserved covariates were not confounders

Methodology

IPTW Covariates

- SES
- household structure
- Race/ethnicity (Black and Hispanic)
- Gender
- Parents contacted about behavior in 8^{th} grade
- Parents contacted about 8^{th} grade academic performance
- 8^{th} grade advanced math course-taking
- 8^{th} grade math grades
- Parental college expectations

Analysis Covariates

- High ISS social control school
- ISS
- School social order
- Freshman year math score
- SES
- Gender: female
- Race: Black
- Race: Hispanic
- Absences
- Classes skipped

Research Questions

- What are the short-term (math achievement) and long-term (college attendance) effects associated with attending a high-suspension high school and how are these impacts related?
- How do the effects associated with directly receiving a suspension differ from the indirect effects associated with attending a high-suspension high school?
- How do student background characteristics interact with high-suspension schools when predicting college attendance?

Analysis Structure

4 Models: Unconditional Model, Null Model, Treatment Model, then Selection Model
Repeated for each DV: 11th Grade Mathematics Assessment in Algebraic Reasoning (Multiple Regression), College Entry (Logistic Regression)

Results: Descriptive

	Math Achievement Models				College Attendance Models			
	Treatment Group		Control Group		Treatment Group		Control Group	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
College Attendance					0.61	0.49	0.70	0.46
Low College Expectation					0.39	0.49	0.38	0.49
School Social Order	-0.17	1.01	0.39	0.98	-0.16	1.01	0.40	1.01
SES Quintile	0.11	1.42	0.15	1.42	0.18	1.43	0.19	1.45
Gender: Female	0.50	0.50	0.51	0.50	0.51	0.50	0.52	0.50
Race: Black	0.23	0.42	0.22	0.41	0.22	0.41	0.19	0.39
Race: Hispanic	0.20	0.40	0.19	0.39	0.18	0.39	0.18	0.39
In-School Suspension	0.34	0.76	0.00	0.00	0.31	0.73	0.00	0.00
Absences	1.55	1.07	1.44	1.02	1.52	1.05	1.42	1.02
Classes Skipped	0.36	0.86	0.25	0.67	0.33	0.81	0.22	0.62
Freshman Year Math Score	-0.90	9.91	0.22	9.92	0.06	9.72	1.34	9.66
Junior Year Math Score	-1.73	9.69	0.84	9.77	-0.89	9.66	1.86	9.60
Observations	3,890		3,800		4,080		3,850	

Note: Due to slight differences between W2W1STU weights (Math Achievement Models) and W3W1W2STUTR weights (College Attendance Models), variable means and standard deviations have been listed separately. Also, unweighted population statistics, such as the number of observations, have been rounded to the nearest ten to comply with our restricted use data license agreement.

Results: Unconditional Model

	Math Achievement: Treatment Model	Math Achievement: Selection Model	College Attendance: Treatment Model	College Attendance: Selection Model
High-Suspension School	-6.67(0.58)***	-2.57(0.64)***	0.31(0.04)***	0.67(0.09)**
Intercept	2.81(0.43)***	0.84(0.47)	3.61(0.34)***	2.36(0.25)***
Observations	7,830	7,830	7,900	7,920

Notes: For Math Achievement Models, coefficients are provided, which are followed by robust standard errors in parentheses. For College Attendance Models, odds ratios are provided, which also are followed by robust standard errors in parentheses.
**p <.05, **p <.01, ***p <.001*

Regression Analysis of High-Suspension School Impact on Math Scores

	Model 1 (Null Model)	Model 2 (Treatment Model)	Model 3 (Selection Model)
High-Suspension School		-1.81(0.37)***	-1.45(0.38)***
In-School Suspension	-1.17(0.24)***	-0.78(0.25)**	-0.92(0.25)***
School Social Order	0.31(0.16)	0.11(0.16)	0.09(0.17)
Freshman Year Math Score	0.66(0.02)***	0.66(0.02)***	0.66(0.02)***
SES Quintile	0.73(0.10)***	0.63(0.11)***	0.59(0.11)***
Gender: Female	-0.44(0.23)	-0.46(0.23)*	-0.45(0.26)
Race: Black	-1.20(0.32)***	-0.97(0.31)**	-1.13(0.36)**
Race: Hispanic	-0.02(0.40)	-0.10(0.40)	-0.32(0.46)
Absences	-0.65(0.12)***	-0.64(0.11)***	-0.68(0.12)***
Classes Skipped	0.12(0.17)	0.07(0.17)	0.08(0.17)
Intercept	1.32(0.28)***	2.18(0.33)***	2.16(0.39)***
Observations	7,680	7,680	7,680

Note: Coefficients Followed by Robust Standard Errors in Parentheses
**p <.05, **p <.01, ***p <.001*

Null Models: Logistic Regressions of Analysis Covariates on College Attendance

	Model 4	Model 5	Model 6
In-School Suspension	0.58(0.08)***	0.64(0.08)***	0.68(0.08)**
School Social Order	1.12(0.07)	1.10(0.07)	1.08(0.07)
Low College Expectation	0.36(0.03)***	0.43(0.04)***	0.46(0.05)***
SES Quintile	1.67(0.06)***	1.55(0.05)***	1.51(0.05)***
Gender: Female	1.30(0.12)**	1.34(0.13)**	1.42(0.14)***
Race: Black	0.84(0.10)	1.00(0.12)	1.09(0.13)
Race: Hispanic	0.95(0.14)	0.94(0.14)	0.95(0.14)
Absences	0.74(0.04)***	0.74(0.04)***	0.76(0.04)***
Classes Skipped	0.81(0.07)*	0.83(0.07)*	0.82(0.07)*
Freshman Year Math Score		1.05(0.01)***	1.01(0.01)
Junior Year Math Score			1.07(0.01)***
Intercept	5.06(0.60)***	5.54(0.56)***	4.17(0.52)***
Observations	7,900	7,900	7,900

Note: Odds Ratios Followed by Robust Standard Errors in Parentheses
**p <.05, **p <.01, ***p <.001*

Treatment Models: Non-IPTW Logistic Regressions of the Impact of High-Suspension Schools on College Attendance

	Model 7	Model 8	Model 9
High-Suspension High School	0.56(0.07)***	0.60(0.07)***	0.67(0.08)**
In-School Suspension	0.67(0.08)**	0.72(0.08)**	0.75(0.09)*
School Social Order	1.05(0.07)	1.04(0.07)	1.04(0.07)
Low College Expectation	0.36(0.03)***	0.42(0.04)***	0.45(0.05)***
SES Quintile	1.62(0.06)***	1.52(0.05)***	1.48(0.05)***
Gender: Female	1.30(0.12)**	1.34(0.13)**	1.42(0.13)***
Race: Black	0.93(0.11)	1.09(0.13)	1.16(0.15)
Race: Hispanic	0.91(0.13)	0.91(0.13)	0.93(0.14)
Absences	0.75(0.04)***	0.74(0.04)***	0.76(0.04)***
Classes Skipped	0.80(0.07)**	0.82(0.07)*	0.82(0.07)*
Freshman Year Math Score		1.05(0.01)***	1.01(0.01)
Junior Year Math Score			1.06(0.01)***
Intercept	6.73(0.90)***	5.84(0.78)***	5.10(0.71)***
Observations	7,900	7,900	7,900

Note: Odds Ratios Followed by Robust Standard Errors in Parentheses

**p <.05, **p <.01, ***p <.001*

Selection Models: IPTW Logistic Regressions of the Impact of High-Suspension Schools on College Attendance

	Model 10	Model 11	Model 12
High-Suspension High School	0.76(0.09)*	0.78(0.11)*	0.84(0.11)
In-School Suspension	0.75(0.09)*	0.79(0.09)*	0.84(0.10)
School Social Order	1.11(0.08)	1.11(0.08)	1.11(0.08)
Low College Expectation	0.36(0.04)***	0.42(0.04)***	0.45(0.05)***
SES Quintile	1.66(0.06)***	1.53(0.06)***	1.50(0.05)***
Gender: Female	1.32(0.12)**	1.34(0.13)**	1.41(0.13)***
Race: Black	0.75(0.10)*	0.88(0.13)	0.95(0.13)
Race: Hispanic	0.91(0.12)	0.89(0.12)	0.92(0.13)
Absences	0.76(0.04)***	0.75(0.04)***	0.77(0.04)***
Classes Skipped	0.77(0.06)**	0.80(0.06)**	0.79(0.07)**
Freshman Year Math Score		1.05(0.01)***	1.01(0.01)
Junior Year Math Score			1.06(0.01)***
Intercept	5.59(0.75)***	5.09(0.73)***	4.50(0.65)***
Observations	7,920	7,920	7,920

Note: Odds Ratios Followed by Robust Standard Errors in Parentheses

**p <.05, **p <.01, ***p <.001*

Summary

Q1: What are the short-term (test scores) and long-term (college attendance) impacts associated with attending a high-suspension high school and how are these impacts related?

- High-suspension schools were related to lower than average mathematics test performances.
- High-suspension high schools decreased a student’s odds of attending college; 43% chance versus a 57% chance for high and low suspension schools, respectively.
- Estimates are upwardly biased when not controlling for selection into schools.
- Junior year math scores in the college attendance selection model rendered insignificant the spillover effects associated with attending a high-suspension high school, as well as the direct effects associated with receiving an ISS.

Summary

- Interpretations about those junior math test-score effects on college attendance…

1. Math performances are so important that they are likely to reduce the impact of suspension on college attendance
2. ISS lowers junior year math scores to a point that, when those math scores are considered, they split and render the effects of ISS on college attendance insignificant
3. The relatively larger impact of math to college attendance suggest reductions in ISS (i.e. draining the school-to-prison pipeline) will not alone move more youth into the STEM pipeline. Supporting stronger math performances is absolutely essential.

Summary

Q2: How do the effects associated with directly receiving a suspension differ from the spillover effects associated with attending a high-suspension high school?

- The spillover effects in high-suspension schools on college attendance and math achievement are similar—and at times greater—than the direct effects associated with receiving an ISS.

Q3: How do student background characteristics interact with high-suspension schools when predicting mathematics scores and college attendance?

- Significantly lower math scores remained for Black students in high suspension schools after adjusting for their school selection, with potential indirect consequences for college entry.
- Greater odds of college entry remained for women and high income students after accounting for selection.

Conclusions

- The impact of high-suspension schools on math confirms that restrictive social control is draining the STEM pipeline of diverse talent.
  - RSA transformation may pose consequences for all students
- Given moratoriums on OSS have left ISS as a replacement, our findings related to ISS suggest that schools need to come up with an alternative to the alternative.
  - Restorative justice and practices have shown promising student benefits, but also institutional challenges.
  - Shift reform from schools to police (e.g. Philadelphia Police School Diversion Program)
- Policy and “Racial Reform” must work in-tandem.
  - ABAR/City Garden Montessori School

Limitations and Next Steps

- Availability of appropriate data –HSLS is not ideal
- Other types of social control may yield similar or different results
  - Surveillance, SROs, Exclusion, dress-code, corporal
- School segregation levels may interact with social control levels, especially if the use of social control strategies is a response to the racialization of students.
- Other individual level factors matter (e.g. Disability)

THANKS AND QUESTIONS

Odis Johnson Jr.

o.johnson@wustl.edu

Fatal Interactions with Police Study (FIPS)

https://sites.wustl.edu/fips/

Washington University in St. Louis

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Before

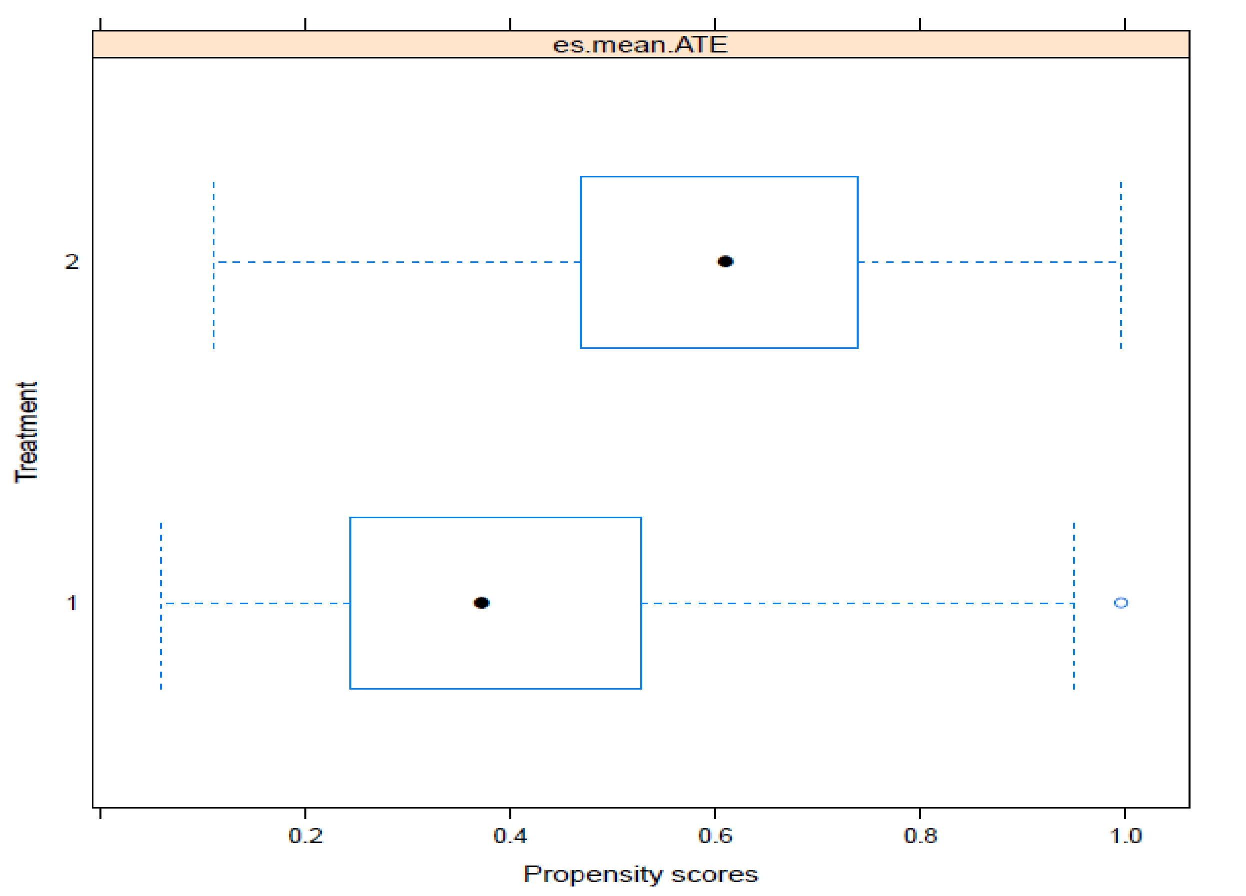
Variable	High-Suspension School	Low-Suspension School	Standardized Difference	P-Value
Race: Black	0.33	0.14	0.45	0.00
Race: Hispanic	0.22	0.21	0.03	0.46
Gender: Female	0.48	0.52	-0.09	0.01
SES Quintile	2.64	3.53	-0.62	0.00
Two Parent Household	0.67	0.83	-0.35	0.00
High Parental College Expectations	0.63	0.79	-0.34	0.00
8th Grade Behavior	1.52	1.25	0.37	0.00
8th Grade Performance	1.45	1.31	0.20	0.00
8th Grade Math Course	3.27	3.48	-0.11	0.00
8th Grade Math Grade	2.25	1.92	0.33	0.00
Observations	4,150	4,710		
ESS	2,052.88	1,949.67		

After

Variable	High-Suspension School	Low-Suspension School	Standardized Difference	P-Value
Race: Black	0.24	0.22	0.03	0.45
Race: Hispanic	0.21	0.21	0.00	0.99
Gender: Female	0.50	0.49	0.01	0.72
SES Quintile	3.06	3.11	-0.04	0.26
Two Parent Household	0.75	0.75	0.00	0.91
High Parental College Expectations	0.72	0.73	-0.04	0.34
8th Grade Behavior	1.37	1.37	0.01	0.86
8th Grade Performance	1.36	1.38	-0.02	0.70
8th Grade Math Course	3.36	3.35	0.00	0.88
8th Grade Math Grade	2.08	2.08	0.00	1.00
Observations	4,150	4,710		
ESS	2,027.64	1,405.51		

Sensitivity Analysis

Removed Treatment Covariate	Comparison	Outcome	Sensitivity Results	Original Results
Race: Black	Model #3	Math Achievement (coefficient)	-1.39(0.37)***	-1.45(0.38)***
Race: Black	Model #10	College Attendance (odds ratio)	0.77(0.09)*	0.76(0.09)*
Race: Hispanic	Model #3	Math Achievement (coefficient)	-1.45(0.38)***	-1.45(0.38)***
Race: Hispanic	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*
Gender: Female	Model #3	Math Achievement (coefficient)	-1.44(0.38)***	-1.45(0.38)***
Gender: Female	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*
SES Quintile	Model #3	Math Achievement (coefficient)	-1.19(0.38)**	-1.45(0.38)***
SES Quintile	Model #10	College Attendance (odds ratio)	0.83(0.10)	0.76(0.09)*
Two Parent Household	Model #3	Math Achievement (coefficient)	-1.46(0.38)***	-1.45(0.38)***
Two Parent Household	Model #10	College Attendance (odds ratio)	0.77(0.09)*	0.76(0.09)*
High Parental College Expectations	Model #3	Math Achievement (coefficient)	-1.46(0.38)***	-1.45(0.38)***
High Parental College Expectations	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*
8^{th} Grade Performance	Model #3	Math Achievement (coefficient)	-1.45(0.37)***	-1.45(0.38)***
8^{th} Grade Performance	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*
8^{th} Grade Behavior	Model #3	Math Achievement (coefficient)	-1.44(0.38)***	-1.45(0.38)***
8^{th} Grade Behavior	Model #10	College Attendance (odds ratio)	0.74(0.09)*	0.76(0.09)*
8^{th} Grade Math Course	Model #3	Math Achievement (coefficient)	-1.52(0.37)***	-1.45(0.38)***
8^{th} Grade Math Course	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*
8^{th} Grade Math Grade	Model #3	Math Achievement (coefficient)	-1.53(0.38)***	-1.45(0.38)***
8^{th} Grade Math Grade	Model #10	College Attendance (odds ratio)	0.76(0.09)*	0.76(0.09)*


es.mean.ATE
Treatment
2
1
0.2
0.4
0.6
0.8
1.0
Propensity scores

Consequences for “Practice” too…

- Adultification
- Labeling and self fulfilling prophesy (teachers)
- Cultural capital theories related to “culture policing”
- Labeling and Identity Conformance (students)

The “Pre-K to Prison Pipeline” & Race

Collaborators

Sheretta Butler Barnes, Associate Professor, George Warren Brown School of Social Work, WUSTL

Habiba Ibrahim, Post-doctoral Fellow, WUSTL

Jason Jabbari, Doctoral Candidate, WUSTL

David Barnes, Doctoral Pre-Candidate, WUSTL

Engineering and Education Centers (EEC), and Division on Research on Learning in Formal and Informal Settings (DRL) of the National Science Foundation