FUTURE OF METHODS AND MEASURES IN THE FIELD OF EDUCATION RESEARCH

Testimony for the National Academies of Science, Engineering, and Medicine

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JOHNS HOPKINS

RELEVANT BACKGROUND

- Tenured appointments in African American Studies, Sociology, Education, Public Health
- Director, Institute in Critical Quantitative, Computational, and Mixed Methodologies (ICQCM)
- Executive Director, Hopkins Center for Safe and Healthy Schools
- Principal Investigator: Race, Gender, and Social Control in STEM Lab
- Member, Visiting Panel Educational Testing Services, and Johns Hopkins University AI+X Initiative

CONTEXT

Questions

- From your position in the field, what is the future of methods and measurement in education research in the United States?
- How are those methods and measures positioned (or not) to address equity issues in education?

Moment

- Racialized state violence
- Methods, measurement, and data science are not objective/race neutral – they supply the logics of systemic racism
- Understanding the interrelatedness of racial (in)justice in school and scientific measurement has become a leading concern of equity

OBSERVATIONS

- NCES national longitudinal studies do not include metrics that inform the nation on matters of justice and the carceral condition of U.S. schools. In fact, there has been some regression, on this point, in the capacity of longitudinal studies with individual level data.

- IES databases are not equipped to answer the most important questions about racialized mechanisms or experiences/perceptions of interpersonal and systemic racism

OVERVIEW

- Research about social control in schools
- Education Longitudinal Study: 2002, High School Longitudinal Study: 2009 and Facilities checklist
- Data harmonization of existing IES databases
- Metrics of race, racialization, and experiences of racism in study design

SOCIAL CONTROL

Social Control (Informal)

- Maintenance of social order through the adherence to and **internalization of shared norms** (Durkheim 1961), "internal **group regulation**" (Kirk 2009), and/or a "**repressive moral code**" (Massey 1996)

Formal Social Control

- "**State apparatuses**" (Althusser 1969; Foucault 2009), "**institutional** regulation of life" (Lacombe 1996), and/or the **laws, government** action, and institutions that arise in reaction to perceived deviance (Parsons 1937), "**coercion**" (Janowitz 1975), and "**social control technologies**" (Foucault 1975)

INFRASTRUCTURE OF SOCIAL CONTROL: IT'S…

CULTURAL POLICING	POLICY ENVIRONMENT	TECHNOLOGIES	LAW ENFORCEMENT
POLITICAL ECONOMIC	PUNISHMENT/DISCIPLINE	PEDAGOGICAL	ENDOGENOUS

RACE, GENDER & SOCIAL CONTROL IN STEM LAB

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Karishma Furtado, PhD
Olivia Marcucci, PhD
Jason Jabbari, PhD
David Barnes
Maya Williams, PhD

(NSF #EEC-1833161, #DRL-1800199, #EEC-1619843)

RACE, GENDER AND SOCIAL CONTROL IN STEM LAB

Rationale

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 creativity, collaborative problem solving, interpersonal confidence, engagement, and self-efficacy.

Questions

- Do high-social control schools increase the likelihood of being suspended?
- Do high-social control schools decrease math achievement?
- Do high-social control schools decrease the likelihood of attending college?
- Does considering levels of social control account for race-gender differences in suspensions, math performances, and college enrollment?

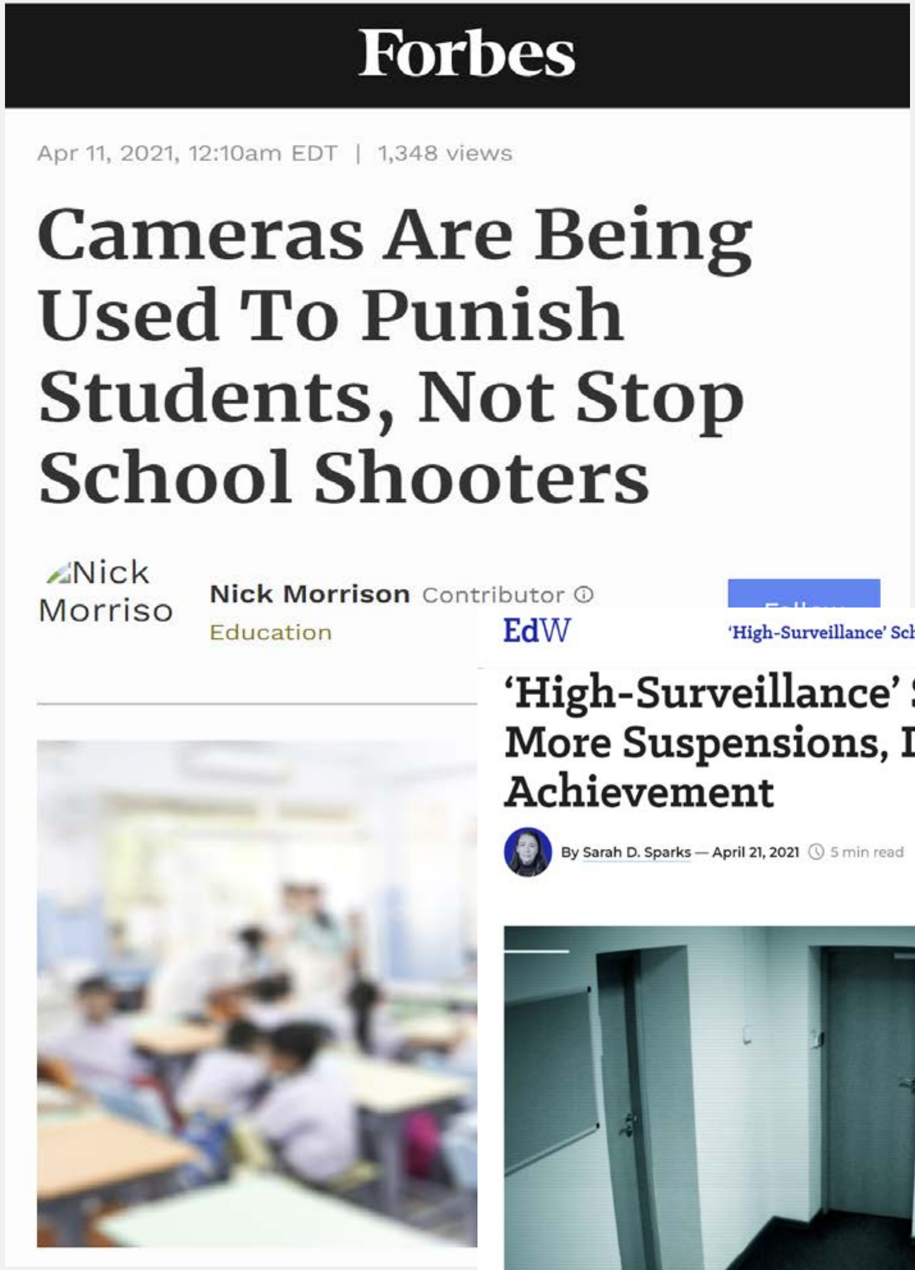
METHODOLOGY

- Counterfactual Modeling
  - An approach to derive causal inferences from seemingly observational data (Morgan and Winship 2007; Johnson and Wagner 2017).
- Machine Learning Estimated 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 administrative reports of *surveillance* (metal detector and camera), *searches* (having random metal detector checks; random dog sniffs; random contraband sweeps; and drug testing), and, *security* (closing the campus for lunch; requiring uniforms; enforcing strict dress codes; requiring clear book bags; requiring identification badges for students) to create a school average.
- Based on this measure, high schools were segmented into thirds.
- The highest third (3,708 students) was operationalized as high-social control schools, while the lowest third (4709 students) was operationalized as low-social control schools (1 = high-social control school; 0 = low-social control school).
- Multiple imputation using chained equations (MICE) is used to address missing values of independent variables only


Forbes

Apr 11, 2021, 12:10am EDT | 1,348 views

Cameras Are Being Used To Punish Students, Not Stop School Shooters

Nick Morrison Contributor

Education


EdW 'High-Surveillance' Schools Lead to More Suspensions, Lower Achievement

'High-Surveillance' Schools Lead to More Suspensions, Lower Achievement

By Sarah D. Sparks — April 21, 2021 5 min read

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- Black enrollment at high-social control schools (HSCS) is 24% compared to only 6% at low-social control schools (LSCS).
- Attending a HSCS increases the odds of receiving an in-school suspension (OR = 1.42; $p < 0.05$) net of school-level social disorder and individual-level misbehavior, especially for Black-males (OR = 3.20; $p < 0.05$) and Black females (OR = 1.99; $p < 0.05$).
- Twelfth grade math test scores are significantly lower in HSCS (-1.51; p < 0.05).
- HSCS significantly decreases college attendance (OR = 0.82 p < 0.05)
- Black females become more likely to attend college (OR = 1.74; p < 0.05) and the reduced likelihood for Black males becomes insignificant when 12th grade math tests scores and suspensions are considered

HIGH SCHOOL LONGITUDINAL STUDY: 2009

Did not include the facilities checklist in data collection unlike its predecessor, the ELS 2002:

- Built environment
- Security and safety procedures
- Technological infrastructure of schools
- Aspects and levels of social disorder

NSF Grants - Social Control

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), “Supplement to Race-Gender Trajectories in Engineering: The Role of Social Control across Neighborhood and School Contexts.”

Improving federal data for social control research

Data harmonization of 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)

INSTITUTE IN CRITICAL QUANTITATIVE, COMPUTATIONAL, AND MIXED METHODOLOGIES

Johns Hopkins University

Vanderbilt University

The University of Pennsylvania

ICQCM

CRITICAL DATA SCIENCE FOR A DIVERSE WORLD

NSF #ECR-EHR 1937687/1937490/1937391, Spencer Foundation #202000127, and William T. Grant Foundation #190932

HOW CAN RESEARCHERS EXAMINE THE SOCIAL STRUCTURE OF RACE WITH LONGITUDINAL STUDIES THAT FAIL TO ASK PARTICIPANTS ABOUT IT?

- Race/ethnicity, as a category
- Processes of racialization
- Racial identity and beliefs
- Experiences with race/racism

HIGH SCHOOL LONGITUDINAL STUDY 2009

Copy of HSLS09_VariableList_BY-2013U-HSTranscripts - Last Modified: 3/18/2017

	A	B	C	D	E
96	M1ENGCOMP	M1 D01A Comparison of females' and males' abilities in English or language arts		P	"Males are much better" recoded as "Males are somewhat to much better" on
97	M1MTHCOMP	M1 D01B Comparison of females' and males' abilities in math		P	"Males are much better" recoded as "Males are somewhat to much better" on
98	M1SCICOMP	M1 D01C Comparison of females' and males' abilities in science		P	
99	M1TARDY	M1 D02A Student tardiness is a problem at this school		P	
00	M1STUABSENT	M1 D02B Student absenteeism is a problem at this school		P	
01	M1CUT	M1 D02C Student class cutting is a problem at this school		P	
02	M1TCHRABSENT	M1 D02D Teacher absenteeism is a problem at this school		P	"Serious problem" recoded as "Moderate to serious problem" on the public us
03	M1DROPOUT	M1 D02E Students dropping out is a problem at this school		P	
04	M1APATHY	M1 D02F Student apathy is a problem at this school		P	
05	M1INVOLVEMNT	M1 D02G Lack of parental involvement is a problem at this school		P	
06	M1UNPREPPROB	M1 D02H Students coming unprepared to learn is a problem at this school		P	
07	M1HEALTH	M1 D02I Poor student health is a problem at this school		P	
08	M1RESOURCES	M1 D02J Lack of teacher resources and materials is a problem at this school		P	
09	M1ABLRANGE	M1 D03A Teaching is limited by different academic abilities in the same class		P	
10	M1SESRANGE	M1 D03B Teaching is limited by students with wide range of SES backgrounds		P	
11	M1LANGRANGE	M1 D03C Teaching is limited by students with wide range of language backgrounds		P	
12	M1SPECNEED	M1 D03D Teaching is limited by students with special needs		P	
13	M1UNINTEREST	M1 D03E Teaching is limited by uninterested students		P	
14	M1MORALE	M1 D03F Teaching is limited by low morale among students		P	
15	M1DISRUPT	M1 D03G Teaching is limited by disruptive students		P	
16	M1PROFDEV	M1 D03H Teaching is limited by inadequate professional learning opportunities		P	
17	M1ADMSUPPORT	M1 D03I Teaching is limited by inadequate administrative support		P	
18	M1COMPUTER	M1 D03J Teaching is limited by shortage of computer hardware/software		P	
19	M1TECHSUPPRT	M1 D03K Teaching is limited by shortage of support for using computers		P	
20	M1BOOKS	M1 D03L Teaching is limited by shortage of textbooks for student use		P	
21	M1STUEQUIP	M1 D03M Teaching is limited by shortage of instructional equipment for students		P	
22	M1DEMOEQUIP	M1 D03N Teaching is limited by shortage of equipment for demonstrations		P	
23	M1FACILITIES	M1 D03O Teaching is limited by inadequate physical facilities		P	
24	M1RATIO	M1 D03P Teaching is limited by high student to teacher ratio		P	
25	M1PLANNING	M1 D03Q Teaching is limited by lack of planning time		P	
26	M1AUTONOMY	M1 D03R Teaching is limited by lack of autonomy in instructional decisions		P	
27	M1FAMSUPPORT	M1 D03S Teaching is limited by lack of parent/family support		P	
28	M1FAMILY	M1 D04A Amount a student can learn is primarily related to family background		P	

BY Parent Instrument Variables | F1 Parent Instrument Variables | BY Teacher Variables | BY Administ...

FUTURE METRICS FOR EQUITY

- Facilities checklist should be implemented for all IES national longitudinal studies that collect individual level student data
  - A step further would include SSO techniques since the facilities checklist is but one snapshot in time
- Collect data on other dimensions of social control and justice
- National longitudinal studies should move beyond measures that reflect race as a category toward measures of:
  - Race as a process – "racialization"
  - Race/ethnic identity and beliefs
  - Individual experiences/perceptions of racism

THANKS AND QUESTIONS

Work featured in this presentation was funded by NSF grants DGE -1937687/1937490/1937391, EEC-1833161, DRL-1800199, EEC-1619843, and DRL-0941014 however the conclusions are solely those of the PI.

Published/Forthcoming (Articles Only)

- Johnson, Jr., O. and Jason Jabbari. Forthcoming. "The Racialized Interaction of School Suspension, Math Performance, and Math Self-Efficacy in Majority White Schools." *Educational Forum*.
- Jabbari, Jason and O. Johnson Jr. 2021. "The Process of 'Pushing Out': Accumulated Disadvantage across School Punishment and Math Achievement Trajectories." *Youth & Society*, https://doi.org/10.1177/0044118X211007175.
- Jabbari, Jason and O. Johnson, Jr. 2020. "The Collateral Damage of In-School Suspensions: A Counterfactual Analysis of High-Suspension Schools, Math Achievement and College Attendance." *Urban Education*, https://doi.org/10.1177/0042085920902256
- Ibrahim, Habiba and O. Johnson, Jr. 2020. "School Discipline, Race-Gender, and STEM Readiness: A Hierarchical Analysis of the Impact of School Discipline on Math Achievement in High School." *The Urban Review*, 52(1), 75-99
- Jabbari, Jason and O. Johnson, Jr. 2020. "Veering Off Track in US High Schools? Redirecting Student Trajectories by Disrupting Punishment and Math Course-taking Tracks." *Child and Youth Services Review*. https://doi.org/10.1016/j.childyouth.2019.104734
- Johnson, Jr., O., J. Jabbari, M. Williams and O. Marcucci. 2019. "Disparate Impacts: Balancing the Need for Safe Schools with Racial Equity in Discipline." *Policy Insights from Behavioral and Brain Sciences,* Vol 6(2), 162-169

Under Review (Articles Only)

- Jabbari, Jason and O. Johnson Jr. "Multiplying Disadvantages in U.S. High Schools: An Intersectional Analysis of the Interactions among Punishment and Achievement Trajectories."
- Johnson, Jr., O., H. Ibrahim and J. Jabbari. "The Infrastructure of Black Social Control: A Multi-Level Counterfactual Analysis of Surveillance, Punishment, and Educational Inequality."
- Furtado, Karishma, Sarah Murphy, Jason Purnell, O. Johnson Jr., and Ross Brownson. "Learning to disengage: Racial disparities in discipline, social control in school, and voting activity."
- Ibrahim, Habiba, D. Barnes, S. Butler-Barnes, O. Johnson Jr. Forthcoming. "Black Girls, Strict School Dress Code and Math Course Taking in High Schools." *Social Sciences*.

References

- Ingels, S., Pratt, D., Herget, D., Burns, L., Dever, J., Ottem, R., Rodgers, J., Jin, Y. & Leinwand, S. 2011. High School Longitudinal Study of 2009: Base-Year Data File Documentation. NCES 2011-328. *National Center for Education Statistics*.
- Janowitz, M. 1975/1991. *On Social Organization and Social Control.* Chicago: University of Chicago Press.
- Johnson, Jr., O. 2012. "Relocation Programs, Opportunities to Learn and the Complications of Conversion." *Review of Educational Research*, *82 (2): 131-178 (JCR Impact Factor: 8.24*). in Year-Round and 9-Month Schools." *Annals of the American Academy of Political and Social Science, 674, 1, 240-261*
- Johnson, Jr., O. 2012. "A Systematic Review of Neighborhood and Institutional Relationships Related to Education." *Education and Urban Society*, *44 (4): 477-511*
- Johnson, Jr., O and M. Wagner. 2017. "Equalizers or Enablers of Inequality? A Counterfactual Analysis of Racial and Residential Test-Score Gaps in Year-Round and 9-Month Schools." *Annals of the American Academy of Political and Social Science, 674, 1, 240-261*
- Johnson, Jr., O., Christopher St. Vil, Keon Gilbert, Melody Goodman and Cassandra Arroyo Johnson. 2019. "How Neighborhoods Matter in Fatal Interactions between Police and Men of Color." *Social Science and Medicine, 220, January, Pages 226-235.*
- Johnson, Jr., O. and V. Nebbitt. 2015. "A Framework for Inquiry into Neighborhood-Institutional Relationships Related to Public Housing and Adolescent Development." In "Adolescents and Public Housing: Addressing Psychological and Behavioral Health" edited by Von E. Nebbitt. New York: Columbia University Press.
- Kirk, D. S. 2009. Unraveling the contextual effects on student suspension and juvenile arrest: The independent and interdependent influences of school, neighborhood, and family social controls. *Criminology*, 47(2), 479-520.
- Kupchik, A. (2010). *Homeroom Security: School Discipline in an Age of Fear*. New York: New York University Press.
- Lacoe, J., & Steinberg, M. P. (2018). Do Suspensions Affect Student Outcomes? *Educational Evaluation and Policy Analysis*. Published online.

References

- Lacombe, D. 1996. Reforming Foucault: A Critique of the Social Control Thesis. The British Journal of Sociology, Vol. 47, No. 2, pp. 332-352
- Losen, D., and Martinez, T. 2013. Out of school and off track: The overuse of suspensions in American middle and high schools. *The Center for Civil Rights Remedies.*
- Losen, Daniel, Cheri Hodson, Michael A. Keith II, Katrina Morrison, and Shakti Belway 2015. Are we closing the school discipline gap? The Center for Civil Rights Remedies at the Civil Rights Project. CA: UCLA.
- Massey, D. 1996. The Age of Extremes: Concentrated Affluence and Poverty in the Twenty-First Century. *Demography* Vol. 33, No. 4, pp. 395-412
- Morgan, Stephen and Christopher Winship. 2007. *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. Cambridge: Cambridge University Press.
- Parsons, Talcott. 1937. The Structure of Social Action. New York: McGraw-Hill. . 1951. The Social System. Glencoe, Ill.: Free Press.
- Peguero, A. A., Varela, K. S., Marchbanks III, M. P. T., Blake, J., & Eason, J. M. (2018). School Punishment and Education: Racial/Ethnic Disparities with Grade Retention and the Role of Urbanicity. *Urban Education*.
- Perry, B. and Morris, E. 2014. Suspending Progress: Collateral Consequences of Exclusionary Punishment in Public Schools. *American Sociological Review*, 79, 1067-87.
- Robers, S., Kemp, J., Rathbun A., Morgan, R. & Snyder, T. (2014). *Indicators of School Crime and Safety: 2013.* National Center for Educational Statistics, U.S. Department of Education.
- U.S. Department of Education, Office for Civil Rights Data Collection, 2015-16
- U.S. Department of Education, National Center for Education Statistics. 2019. *Indicators of School Crime and Safety: 2018* (NCES 2019-047).
- Western, Bruce and Becky Pettit 2010. Incarceration & social inequality. Daedalus, https://www.amacad.org/publication/incarceration-social-inequality

SUPPLEMENTAL SLIDES

CARCERAL ECOSYSTEM

- Mass incarceration in the U.S. (Alexander 2010)
  - Risk of incarceration is greatest in minoritized communities (Clear 2007)
    - Odds of a police encounter appear greatest for youth in schools (Ferris 2015)
      - Racial disparities in discipline, pushout, and referral are prominent (OCR 2014; Losen et al. 2015; Johnson et al. 2019)
        - Disastrous consequences for equity in school outcomes and college entry (Johnson and Jabbari 2021; Jabbari and Johnson 2020a, 2021b; Ibrahim, Johnson, and Jabbari 2020)

Methodology

Creating the Treatment

- Used administrative reports of *surveillance* (metal detector and camera), *searches* (having random metal detector checks; random dog sniffs; random contraband sweeps; and drug testing), and, *security* (closing the campus for lunch; requiring uniforms; enforcing strict dress codes; requiring clear book bags; requiring identification badges for students) to create a school average.
- Based on this measure, high schools were segmented into thirds.
- The highest third (3,708 students) was operationalized as high-social control schools, while the lowest third (4709 students) was operationalized as low-social control schools (1 = high-social control school; 0 = low-social control school).
- Multiple imputation using chained equations (MICE) is used to address missing values of independent variables only

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 - GBM

- Generalized boosted modeling (GBM) (see Drake 1993; Freedman and Berk 2008; McCaffrey, Ridgeway, and Morral 2005).
- GBM (see Drake 1993; Freedman and Berk 2008; McCaffrey, Ridgeway, and Morral 2005) utilizes automated, data adaptive modeling algorithms to “predict treatment assignment from a large number of pretreatment covariates while also allowing for flexible, non-linear relationships between the covariates and the propensity score” (p. 3).
- Generalized Boosting Models repeatedly fit many decision trees to improve the accuracy of the model. For each new tree in the model, a random subset of all the data is selected using the boosting method.
- Utilized the TWANG—Toolkit for Weighting and Analysis of Non-equivalent Groups—package (Ridgeway, McCaffrey, Morral, Burgette, & Griffin, 2014) in STATA for the estimation of the propensity score weights for the treatment.
- TWANG’s default settings were used, which include 1000 iterations, three-way interactions among covariates, a shrinkage value of 0.01 to yield a smooth fit, and analytic approximations for Kolmogorov-Smirnov (KS) statistics.
- Mean effect sizes and max KS statistics were used to assess covariate balance. TWANG also provides the comparable sample sizes for both treatments—known as the effective sample size (ESS) (McCaffrey et al., 2005).

PSW Balance Statistics

Unweighted by Propensity Scores

Variables	Treatment	Std.dev.	Control	Std.dev.	Std.diff.	p-value
Neighborhood Crime	2.85	0.41	2.90	0.34	-0.13	0.00
Neighborhood Safety	1.41	0.60	1.32	0.65	0.16	0.00
SES	-0.06	0.69	0.09	0.74	-0.20	0.00
Female	1.49	0.50	1.48	0.50	0.03	0.30
Black	0.24	0.43	0.06	0.23	0.52	0.00
Learning disability	0.12	0.32	0.12	0.32	0.00	0.89
English is 1st Language	0.88	0.32	0.87	0.34	0.05	0.04
Hispanic	0.12	0.33	0.15	0.36	-0.09	0.00
Neighborhood Social Order	5.27	0.94	5.44	1.05	-0.17	0.00
Repeated Grade	0.13	0.34	0.09	0.28	0.13	0.00
Two parent household	0.27	0.44	0.23	0.42	0.09	0.00
Urban School Location	0.32	0.47	0.27	0.44	0.12	0.00

Weighted by Propensity Scores

Neighborhood Crime	2.88	0.37	2.88	0.36	-0.02	0.57
Neighborhood Safety	1.35	0.57	1.34	0.56	0.02	0.54
SES	0.02	0.71	0.04	0.72	-0.02	0.41
Female	1.49	0.50	1.48	0.50	0.01	0.67
Black	0.14	0.35	0.12	0.32	0.06	0.07
Learning disability	0.12	0.32	0.12	0.32	0.00	0.94
English is 1st Language	0.88	0.32	0.87	0.33	0.02	0.53
Hispanic	0.13	0.34	0.14	0.35	-0.03	0.34
Neighborhood Social Order	5.32	0.95	5.36	0.91	-0.04	0.21
Repeated Grade	0.11	0.31	0.10	0.30	0.03	0.26
Two parent household	0.24	0.43	0.24	0.43	0.01	0.83
Urban School Location	0.29	0.45	0.29	0.45	0.00	0.97

Sensitivity Results

Removed Treatment Covariate	Model Type	Outcome	Sensitivity Results	Original Results
Race: Black	Unconditional	Math Achievement (coefficient)	-2.70(0.63)***	-2.50(0.64)***
Race: Black	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
Race: Hispanic	Unconditional	Math Achievement (coefficient)	-2.49(0.64)***	-2.50(0.64)***
Race: Hispanic	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
Gender: Female	Unconditional	Math Achievement (coefficient)	-247(0.64)***	-2.50(0.64)***
Gender: Female	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
SES Quintile	Unconditional	Math Achievement (coefficient)	-3.14(0.62)***	-2.50(0.64)***
SES Quintile	Unconditional	College Attendance (odds ratio)	0.57(0.07)***	0.67(0.09)**
Urban School Location	Unconditional	Math Achievement (coefficient)	-2.57(0.64)***	-2.50(0.64)***
Urban School Location	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
Two Parent Household	Unconditional	Math Achievement (coefficient)	-2.51(0.64)***	-2.50(0.64)***
Two Parent Household	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
High Parental College Expectations	Unconditional	Math Achievement (coefficient)	-2.55(0.64)***	-2.50(0.64)***
High Parental College Expectations	Unconditional	College Attendance (odds ratio)	0.67(0.09)**	0.67(0.09)**
8th Grade Performance	Unconditional	Math Achievement (coefficient)	-2.47(0.64)***	-2.50(0.64)***
8th Grade Performance	Unconditional	College Attendance (odds ratio)	0.68(0.09)**	0.67(0.09)**
8th Grade Behavior	Unconditional	Math Achievement (coefficient)	-2.54(0.64)***	-2.50(0.64)***
8th Grade Behavior	Unconditional	College Attendance (odds ratio)	0.64(0.08)**	0.67(0.09)**
8th Grade Math Course	Unconditional	Math Achievement (coefficient)	-2.76(0.64)***	-2.50(0.64)***
8th Grade Math Course	Unconditional	College Attendance (odds ratio)	0.66(0.09)**	0.67(0.09)**
8th Grade Math Grade	Unconditional	Math Achievement (coefficient)	-2.56(0.64)***	-2.50(0.64)***
8th Grade Math Grade	Unconditional	College Attendance (odds ratio)	0.68(0.09)**	0.67(0.09)**

Descriptive Statistics

Dependent Variables	
College Attendance	0.59(0.49)
12th grade Math Test Scores	51.02 (10.10)
In-School Suspension	0.10(0.29)
Treatment	
High Social Control School	0.44(0.50)
Treatment Components	
Surveillance	0.48(0.56)
Searches	0.93(1.05)
Security	2.00(1.50)
Covariates	
School Social Order (centered)	15.04(6.62)
Student Behavior (centered)	5.02(2.19)
Student Achievement Ideology	4.83(1.16)
Peer Achievement Ideology	2.87(2.72)
Parent Belief in Students	2.46(0.66)
Teacher Belief in Students	1.70(0.81)
Black Males	0.06(0.25)
Black Females	0.06(0.25)

Fixed Effects	Model 1
High Social Control School	1.42(0.19)**
School Social Order	1.01(0.01)
Student Behavior	1.38(0.03)***
Student Achievement Ideology	0.95(0.05)
Peer Achievement Ideology	1.08(0.02)***
Parent Belief in Students	0.91(0.07)
Teacher Belief in Students	1.00(0.07)
Black Males	3.20(0.47)***
Black Females	1.99(0.36)***
Intercept	0.01(0.004)
Random Effects	
Random Intercept Variance	5.64e-34 (3.81e-34)

Note: Odds ratios followed by standard errors in parentheses.
* = p < 0.05; ** = p < 0.01; *** = p < 0.001

Mixed Effects Logistic Regression Models Predicting In-School Suspension

MIXED EFFECTS GENERALIZED LINEAR REGRESSION MODELS PREDICTING MATH SCORES

Variable list	Model 2	Model 3
Fixed Effects		
High Social Control School	-1.52(0.49)**	-1.36(0.48)**
School Social Order	-0.17(0.04)***	-0.17(0.04)***
Student Behavior	-0.70(0.06)***	-0.53(0.07)***
Student Achievement Ideology	0.04(0.13)	0.02(0.13)
Peer Achievement Ideology	-0.32(0.06)***	-0.29(0.06)***
Parent Belief in Students	0.28(0.07)	0.22(0.24)
Teacher Belief in Students	1.08(0.10)***	1.07(0.19)***
Black Males	-6.39(0.63)***	-5.84(0.62)***
Black Females	-7.84(0.56)***	-7.50(0.56)***
In-School Suspension		-4.95(0.49)***
Intercept	60.23(1.13)***	59.83(1.12)***
Random Effects		
Random Intercept Variance	1.20e-30 (7.05e-31)	1.30e-30 (3.78e-31)**
Residual Variance	88.99(1.88)***	87.02(1.87)***

Note: Odds ratios followed by standard errors in parentheses.
* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$

Mixed Effects Logistic Regression Models Predicting College Attendance

	Model 4	Model 5	Model 6	Model 7
Fixed Effects				
High Social Control School	0.82(0.08)*	0.84(0.08)	0.93(0.08)	0.94(0.08)
School Social Order	0.96(0.01)***	0.96(0.01)***	0.97(0.01)***	0.97(0.01)***
Student Behavior	0.82(0.01)***	0.84(0.01)***	0.86(0.02)***	0.88(0.02)***
Student Achievement Ideology	1.06(0.03)*	1.06(0.03)	1.07(0.04)	1.06(0.04)
Peer Achievement Ideology	0.92(0.01)***	0.93(0.01)***	0.94(0.01)***	0.94(0.01)***
Parent Belief in Students	1.22(0.06)***	1.21(0.06)***	1.23(0.07)***	1.22(0.07)***
Teacher Belief in Students	0.92(0.04)	0.92(0.04)	1.05(0.05)	1.05(0.05)
Black Males	0.47(0.07)***	052(0.07)***	0.86(0.14)	0.90(0.15)
Black Females	0.74(0.10)*	0.79(0.11)	1.74(0.24)***	1.78(0.25)***
In-School Suspension		0.37(0.05)***		0.56(0.07)***
12th Grade Math Scores			1.12(.004)***	1.12(.004)***
Intercept	5.58(1.27)***	5.23(1.21)***	2.46(0.58)***	2.39(0.57)***
Random Effects				
Random Intercept Variance	6.52e-35 (3.70e-35)	5.27e-35 (5.69e-35)	3.54e-35 (3.64e-35)	6.63e-35 (5.19e-35)