Title:

New evidence on the effects of heat, crime, segregation and socioeconomic status on racial test score inequalities

Justification:

Racial achievement gaps are a persistent and disheartening fact in U.S. education. There has been extensive work to characterize these gaps across the U.S. and to understand their correlates (e.g., Reardon, Kalogrides, & Shores, forthcoming). However, research to date has been unable to fully explain the variation in racial achievement gaps across places and to identify concrete recommendations for how to reduce racial inequalities. The four papers in this symposium build on existing research and provide meaningful policy-relevant information about reducing racial achievement gaps.

Each of the four papers studies a contextual (e.g., neighborhood, environmental) factor and how it contributes to racial inequalities in standardized test scores. The first two papers in this symposium study the causal effects of ambient temperature and crime on average test scores and racial test score gaps in U.S. schools and districts. These papers find that exposure to heat and crime are causal predictors of educational outcomes and explain a non-trivial portion of the existing racial achievement gap because minority students are more likely to live in high poverty areas with under resourced schools where they are exposed to these factors. The third paper investigates why affluent communities exhibit larger racial achievement gaps relative to less affluent communities. It explores the characteristics of affluent communities that might confound the correlational relationship and finds that there is no difference in the relationship between SES and achievement for students of different racial/ethnic groups. The last paper studies the effects of multiple types of segregation (e.g., residential vs. school; exposure vs. isolation) on racial and income test score gaps within communities. It finds that exposure to poor peers is the most strongly predictive of gaps by race/ethnicity and income, and attempts to causally attribute changes in test score gaps over time to changes in school segregation over the last ten years.

Together, these papers provide new information about how different aspects of students' home and school contexts contribute to the racial test score gaps we observe. The first two identify measurable, and to some extent manipulable, aspects of students' schools and neighborhoods that negatively affect the test scores of racial minority students. The latter two explore in more depth the relationships between SES, segregation and test scores to guide new hypotheses and studies in these areas. This panel will be of interest to SREE members who research racial achievement gaps, social and environmental context, and standardized testing.

Title:

Heat and Learning

Authors and Affiliations:

Josh Goodman, Harvard University
Michael Hurwitz, The College Board
R. Jisung Park, University of California, Los Angeles
Jonathan Smith, Georgia State University

Background and Research Questions

Students in hotter places tend to exhibit lower levels of standardized achievement for any given age or grade. Whether the physical environment in which learning occurs plays a causal role in this correlation remains unknown. Using a unique longitudinal dataset of over 10 million U.S. PSAT takers, we provide evidence consistent with the possibility that, in the U.S., heat may affect learning directly by altering human physiology and cognition.

Extensive laboratory and medical evidence suggests that even moderately elevated temperatures can impair decision-making and cause substantial discomfort (Mackworth, 1946; Seppanen et al, 2006), and recent evidence suggests hot temperature events can reduce students' cognitive performance in the short run (Graff-Zivin, Neidell, Hsiang, 2017; Park, 2017). Hot classrooms may thus reduce the effectiveness of instructional time through physiological impacts on both students and teachers, making it harder for both to focus and accomplish a given set of learning tasks. In cases of extreme heat, school days may be canceled or students dismissed early, directly reducing the amount of instructional time. Depending on the relative access to defensive investments such as school air conditioning, impacts may or may not be spread equally across racial and socioeconomic groups.

Setting, Data Collection, and Research Design

To estimate the causal impact of cumulative heat exposure on human capital accumulation, we link local daily weather data to test scores of 10 million American students from the high school classes of 2001-14 who took the PSAT, a nationally standardized exam designed to assess students' cumulative learning in high school, at least twice. We also construct the first nationwide measures of school air-conditioning penetration in the U.S. by surveying students and guidance counselors across the country about heat-related conditions in approximately 12,000 high schools.

Student fixed effects regressions identify the impact of heat exposure during the prior school year by leveraging within-student variation in temperature over multiple test takes. Our identification strategy relies on the premise that variation in temperature over successive school years for a given student is uncorrelated with unobserved determinants of learning. We provide evidence consistent with that assumption, showing that selection into test-taking and retaking is not endogenous to temperature, even when controlling for regional trends in warming and secular changes in school quality or student composition.

Findings and Robustness Analyses

We present three primary findings about the impact of heat on human capital accumulation. First, cumulative heat exposure reduces the rate of learning. A 1˚F hotter school year in the year prior to the test lowers scores by approximately 0.2 percent of a standard deviation, or slightly less than one percent of an average student's learning gain over a school year. Extreme heat – for instance, days above 90˚F – appear to be especially disruptive. These effects are precisely estimated, robust to controlling for test-day weather, and not predicted by heat exposure in the year following the test. Only school-day exposure to higher temperatures affects test scores. Hot summers and weekends have little impact on achievement and controlling for such exposure does not shrink the magnitude of the impact of hot school days. This suggests that heat's disruption of instructional time may be responsible for the observed drop in test scores.

Importantly, these learning effects appear to be cumulative and persistent beyond just the year prior to the test. Hot school days two, three and four years prior to the test also lower scores, so that the cumulative effect of elevated temperature over multiple school years is substantially larger than that of a single school year. This suggests that any ex post compensatory investments made by students, parents, or teachers in response to such heat shocks do not fully offset their impacts.

Our second major finding is that school air-conditioning effectively mitigates the impacts of heat on learning. Both variation in the cross section and over time thus suggest school air-conditioning is an effective way to reduce the negative impacts of hot school days. School air-conditioning is more prevalent in perennially warmer parts of the country. However, within climate zones, schools in low-income zip codes are less likely to have adequate air conditioning.

Our third result is that the temperature environment in which learning occurs appears to be a meaningful contributor to racial and geographic achievement gaps. Black and Hispanic students' learning is roughly three times as inhibited by the prior school year's heat compared to the learning of White students. We estimate that between three and seven percent of the gap in PSAT scores between White students and Black or Hispanic students can be explained by differences in the temperature environment experienced by students in each group. These disparities appear to be driven both by school-level investments, such as differential air-conditioning penetration, as well as the geographic distribution of racial minorities whereby Black and Hispanic students overwhelmingly reside in hotter locations than White students.

Implications and Conclusion

Heat-related disruptions thus appear to reduce the rate of human capital accumulation over time. Our estimates, combined with estimates of the achievement-earnings relationship from Chetty et al (2011), suggest that in hot areas such as Houston, TX, the present value of air-conditioning is approximately $2.1 million per year for each 1,000-student high school. Global climate change means however that the private return to air-conditioning will increase by approximately $500,000 per school by 2040-2050 for the median U.S. school, according to our back-of-the-envelope calculations.

That heat has larger impacts on Black and Hispanic students and accounts for a non-trivial proportion of the racial achievement gap are facts not documented previously in the vast literature on racial disparities in educational outcomes (Fryer and Levitt, 2005; Jencks and Phillips, 2011). A substantial proportion of the variation in achievement remains unexplained by traditional socioeconomic variables (Reardon et al, 2017). Our findings suggest that the physical factors such as temperature and the built environment may play a larger role in explaining disparities in achievement than previously realized.

Title:

Crime and Inequality in Academic Achievement across School Districts in the United States

Authors and Affiliations:

Gerard Torrats-Espinosa

Background and Purpose

After reaching unprecedented high levels in the early 1990s, crime and victimization rates in the United States started a sustained decline that brought them to levels not seen since the 1960s. Between 1991 and 2015, the property crime rate fell by 50 percent, the violent crime rate fell by 51 percent, and the homicide rate fell by 54 percent (United States Department of Justice, 2015). Even cities that still today struggle with severe problems of community violence like Chicago and Detroit experienced reductions in their murder rates of at least 30 percent between 1991 and 2015. This progress in making cities safer represents one of the most remarkable improvements in the quality of life in urban America in recent history. While the literature has documented many of the causes of this decline (Levitt, 2014; Zimring, 2006), much less is known about its consequences for individuals and communities. This study aims to fill this gap by estimating the impact of violent crime on the academic achievement of seven birth cohorts of children who lived through the early stages of the crime decline.

The study of violent crime and inequality in academic achievement is motivated by evidence from ethnographic and quantitative studies showing that exposure to violent crime is a key pathway through which growing up in disadvantaged neighborhoods affects children's developmental trajectories (Burdick-Will et al., 2011; Harding, 2009; Harding et al., 2011; Sharkey, 2018). The literature has made remarkable progress documenting the short-term effects of being exposed to local, acute incidents of violent crime on cognitive and non-cognitive outcomes (Sharkey, 2010; Sharkey et al., 2014; McCoy et al., 2015; Heissel et al., 2017), but causal evidence on the longer-term consequences of growing up in a violent context is more limited.

Data and Methods

Using data from the Stanford Education Data Archive (SEDA) and from the FBI's Uniform Crime Report (UCR) program, this study investigates the effect of violent crime on school district-level achievement in English Language Arts (ELA) and Mathematics. The research design exploits geographic variation in achievement and crime across 337 school districts and temporal variation across seven birth cohorts of children born between 1996 and 2002. During these seven years, the violent crime rate fell by 23 percent nationally, and in school districts like Chicago and New York, the decline in violent crime over that period was greater than 35 percent. To produce causal estimates of the effect of crime on students' achievement, the research design leverages exogenous shocks to crime rates arising from the availability of funds to hire police officers in local police departments thorough the Community Oriented Policing Services (COPS) grants program.

Results

The findings indicate that birth cohorts who started elementary school when crime rates were lower in their school district perform better on state accountability tests taken by the end of eighth grade, relative to older birth cohorts of the same school district who started elementary school when violent crime was higher (Figure 2.1).

Figure 2.2 shows OLS and 2SLS estimates (with 95 percent confidence intervals) of the effect of changes in violent crime on changes in achievement. The 2SLS estimates indicate that the overall ELA achievement in the district increased by .04 standard deviations for each 10 percent decline in violent crime. The 2SLS estimate for Mathematics corresponds to a .03 standard deviations increase in achievement for each 10 percent decline in crime (when including the set of controls), although this estimate is imprecisely estimated.

Analyses by race/ethnicity and gender show that the benefits of declining violence are larger among black students, Hispanic students, and males (Figure 2.3). Supplementary analyses indicate that the effect of crime on achievement is not driven by compositional changes in school districts that experienced the greatest crime drops or by changes in school district spending after the receipt of the COPS grants. These findings provide additional evidence on the role that violence plays in shaping the developmental trajectories of children and add to a growing body of work that shows how place and geography structure economic mobility and opportunity in the United States (Chetty et al., 2014; Reardon et al., 2016).

Title:

The Relationship between Racial Achievement Gaps and Affluence in U.S. School Districts

Authors and Affiliations:

Kenneth Shores, The Pennsylvania State University
Demetra Kalogrides, Stanford University

Background

The importance of environments—for example, neighborhoods and schools—for student academic outcomes is widely studied. For example, moving from a high- to low-poverty neighborhood improves both short- and long-term outcomes (Burdick-Will, Ludwig and Raudenbush, 2011; Chetty, Hendren and Katz, 2016; Chetty and Hendren, 2018; Kling, Liebman and Katz, 2007). Local contexts are relevant for student academic outcomes for various reasons, a few of which include crime (Sampson, Raudenbush and Earls, 1997), environmental pollutants (e.g., water and air quality and lead exposure) (Grineski, 2017; Miranda, et al., 2009; Sorensen, et al; 2018), and social networks (Carpiano, 2006). Because race/ethnicity and social class moderate local environments (e.g., Sampson, Raudenbush and Earls, 1997), variation in local context results in unequal outcomes for children (e.g., Card and Rothstein, 2007; Rothstein, 2015).

Another feature of local context that has been shown to predict racial/ethnic test score inequality is the average socioeconomic status of the area. For example, Chetty and colleagues (2018), find that black-white gaps in social mobility are larger on average for boys who grow up in low-poverty neighborhoods. In Reardon, Kalogrides and Shores (2018), the authors find that white-black and white-Hispanic achievement gaps are larger in more affluent school districts. The mechanisms through which inequality in local context explains inequality in academic outcomes is straightforward. In contrast, the mechanisms through which a geographic unit's average socioeconomic status would influence test score inequality are less clear.

Research Questions

Why should the affluence of a geographic region affect racial/ethnic test score inequality? We explore three related lines of inquiry: First, what are the characteristics of more affluent districts that might explain racial/ethnic test score inequality? Second, do these characteristics account for the observed relationship between socioeconomic status and test sore gaps? Finally, is there evidence that equivalent increases to socioeconomic status increase white achievement more than racial/ethnic minority achievement, or do white students, on average, have greater resources, which, in turn, are more effective at translating socioeconomic status into achievement?

Data

District level test score data are based on the results of roughly 200 million standardized math and reading tests administered to elementary and middle school students from 2009-2015 currently available for download at the Stanford Education Data Archive (SEDA). We link these test score data to district level socioeconomic data (gathering multiple variables) available from the American Community Survey (ACS) Education Demographic and Geographic Estimate (EDGE) survey for the survey year 2011-2015, which overlaps with the achievement data. To combine these correlated socioeconomic variables, we construct a composite that is the first principal component of these variables. Finally, to avoid problems of attenuation bias and upward bias resulting from measurement error in right-hand side variables (Abel, 2017), we generate shrunken (Empirical Bayes) estimates of each of the socioeconomic invariables, including the SES composite.

Analysis

Our generic model for understanding the determinants of test score gaps is of the form:

$$Y_i = \alpha + (\mathbf{X}_i)\boldsymbol{\beta} + e_i + v_i; \;\; e_i \sim N[0, \tau]; \;\; v_i \sim N[0, \hat{\omega}_i^2], \tag{1}$$

where Y_i is the estimated white-black or white-Hispanic achievement gap in a U.S. school district i $\mathbf{X}_i$ is a vector of district covariates, discussed in the list above and in the data section. Using the same meta-regression framework, we leverage race-specific data to identify differences in the achievement returns to SES. The generic model is estimated in various parametric and semi-parametric specifications for different ranges of the SES distribution. These models are of the form:

$$Y_{ig} = \alpha_0 + \beta_1 SES_{ig} + \beta_2 Black + \beta_3 Black * SES_{ig} + \beta_4 Hispanic + \beta_5 Hispanic * SES_{ig} + e_{ig} + v_{ig}; \;\; e_{ig} \sim N[0, \tau]; \;\; v_{ig} \sim N\left[0, \hat{\omega}_{ig}^2\right], \tag{2}$$

Results

First (Table 3.1), we show that racial/ethnic socioeconomic inequality is higher in more affluent districts, but racial/ethnic segregation is lower. Thus, there may be factors affecting racial/ethnic test score inequality that also correlate with average socioeconomic status. We then (Table 3.2) show that the positive correlation between racial/ethnic test score gaps and district socioeconomic status is not explained by a host of other factors we consider, including controls for racial/ethnic differences in a variety of socioeconomic indicators, differential exposure to poverty, racial composition, school expenditures, class size, teacher experience, and other school policy variables. We conclude, therefore, that achievement gaps are not larger in more affluent areas due to any of the omitted variables we consider.

Next (Table 3.3), we find that the relationship between white socioeconomic status and white achievement is stronger than the relationship between black/Hispanic socioeconomic status and black/Hispanic achievement. In other words, equivalent increases in socioeconomic status appear to increase white achievement more than black and Hispanic achievement. However, much of the achievement returns to white socioeconomic status occur in regions in which there is no equivalent black and Hispanic income. When we restrict our models (Tables 3.4 and 3.5) to districts within the range of socioeconomic status where the white and black/Hispanic distributions overlap, the relationship between socioeconomic status and achievement among whites, blacks and Hispanics is no different.

Conclusions

We conclude that achievement gaps appear larger in more affluent areas because socioeconomic status is more strongly related to achievement at the top of the socioeconomic status distribution (regions of socioeconomic status for which there are few racial/ethnic minorities) and not because of a differential relationship between socioeconomic status and achievement by race.

Title:

Segregation and Educational Inequality

Authors and Affiliations:

Sean Reardon, Stanford University
Ericka Weathers, The Pennsylvania State University
Demetra Kalogrides, Stanford University
Heewon Jang, Stanford University
Erin Fahle, St. John's University
Jenny Buontempo, Stanford University

Background and Objectives

The empirical evidence documenting the relationship between segregation and academic achievement gaps is scant. Historically, white-black achievement gaps narrowed between the early 1970s and the late 1980s (Reardon, Robinson-Cimpian, & Weathers, 2015) – a time when elementary and secondary schools were also the least segregated in recent history. Studies show that the combination of desegregation and expanded resource exposure for black students partially explains this reduction in the size of white-black achievement gaps (Grissmer, Flanagan, & Williamson, 1998). On the other hand, several cross-sectional studies provide evidence that increases in racial segregation are associated with larger achievement gaps between White and Black students, net of a number of confounding factors (e.g. Card & Rothstein, 2007; Reardon, 2016; Rumberger & Willms, 1992).

Though these studies are informative, their cross-sectional designs cannot account for the possibility that segregation may be confounded with some other unmeasured phenomenon that is also related to racial disparities in academic achievement. In the only longitudinal analysis on the subject that we are aware of, Condron, Tope, Steidl, and Freeman (2013) find that changes in within-state segregation were positively associated with changes in state-level racial disparities in NAEP scores. While their panel design reduces confoundedness, accounts for time-invariant differences between states, and accounts for several relevant economic and educational disparities, their analysis is limited in scope. They examine only state-level achievement, white-black achievement gaps, white-black school segregation, and black students' exposure to other minorities.

With the rise of racial and economic segregation in U.S. public schools over the last 25 years, understanding the effects of segregation on academic achievement of all students is paramount. In this paper, we first use cross-sectional models to examine which of several forms of segregation (e.g., residential vs. school, exposure vs. isolation) are most strongly related to white-black, white-Hispanic, and economically advantaged-disadvantaged achievement gaps and the growth of these gaps across grades at various aggregations (e.g., district, county, metropolitan area, and state). We then leverage a panel design with multiple fixed effects to estimate the effects of these segregation measures on within-cohort year-to-year changes in achievement gaps in districts, counties, and metropolitan areas.

Data and Research Design

The achievement data come from the Stanford Education Data Archive (Version 2.2), which includes nationally normed academic achievement from state accountability reading and mathematics tests taken in grades three through eight between 2009 and 2016 for the universe of school districts in the United States. We use the mean test scores for white, black, Hispanic, economically disadvantaged (ECD), and non-economically disadvantaged (non-ECD) students in our analyses. The segregation measures are estimated using data from the Common Core of

Data (CCD) and the American Community Survey (ACS). The complete list of measures can be seen in the second column of Table 4.1.

Our cross-sectional analyses are executed using precision-weighted hierarchical linear models, run separately at each aggregation. These results provide information about which forms and measures of segregation are most predictive of achievement gaps, and whether these patterns are consistent for the groups studied and the aggregation of the data.

Our panel analyses are executed using crossed fixed effects models. For each unit (district, county, or metro), we compute annual changes in achievement gaps within a cohort (e.g., changes in the gap from third grade in 2009 to fourth grade in 2010). We regress these changes on measures of segregation within the relevant grade-year to estimate the association between segregation in a specific unit-grade-year and the change in the achievement gap in that unit-grade-year. We include unit-by-year and unit-by-grade fixed effects in the model to account for unit-specific trends and differences across grades in factors that may affect achievement gaps. We also control for unit-grade-year specific covariates, including lagged measures of the achievement gap, racial and socioeconomic composition, and the number and size of schools. These models provide estimates of the average association between segregation within a unit-grade-year and the change in the achievement gap during that grade-year. The estimates can be interpreted as causal to the extent that there are no omitted unit-grade-year specific confounders.

Findings

Tables 4.1 and 4.2 show the bivariate and multivariate county-level results for the achievement gaps and gap growth, respectively. The results suggest that, of the segregation measures studied, white-black/Hispanic differences in exposure to poor schoolmates is the strongest predictor of white-black/Hispanic achievement gaps and of growth of gaps across grades. In other words, for racial inequality school segregation appears more important than neighborhood segregation and exposure to poverty appears more important than exposure to minority students. In contrast, poor-non poor H (both residential and school) are the strongest predictors of the ECD gap. Across all models, with and without controls, segregation is consistently predictive of the gaps in grade 3 and the growth of gaps from grade 3 to 8 at all levels of aggregation for both race and ECD gaps.

The panel models are not complete yet, but preliminary analyses show that segregation in a specific grade-year is associated with large growth of gaps in that grade year.

Conclusions

Using data with unprecedented detail and population coverage (approximately 325 million test scores), we show that segregation is highly predictive of achievement gaps. These results are consistent across geographies, groups and with respect to levels and growth of gaps.

Racial differences in exposure to poverty in schools are the most salient for race gaps; residential and school segregation by poverty status most salient for economic disadvantage gaps. Both suggest that difference in exposure to poor classmates is the salient aspect of segregation that leads to unequal academic progress. These results are not definitively causal, but suggest that segregation plays a key role in exacerbating inequality of educational outcomes.

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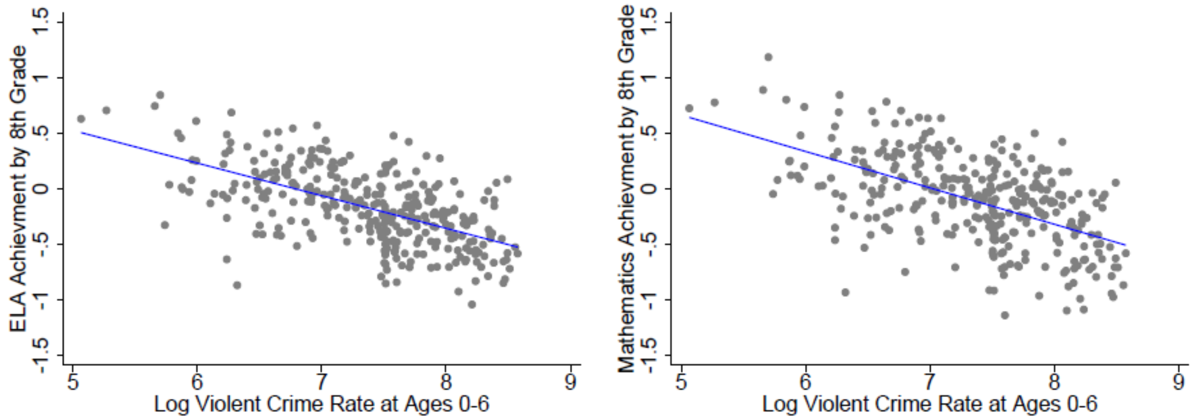
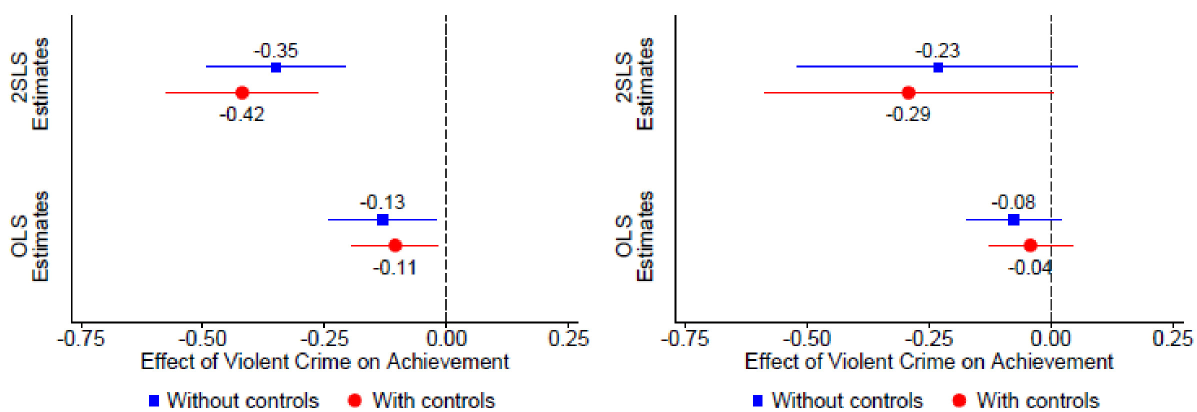
Tables and Figures



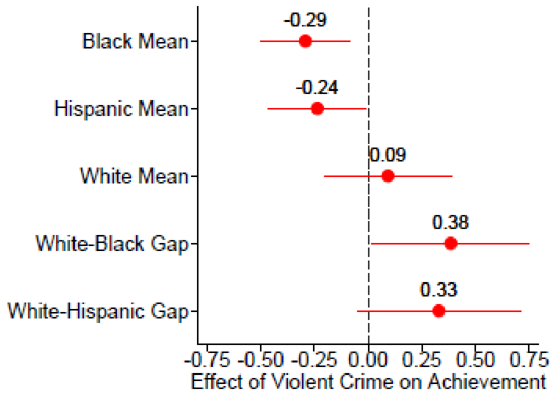
(a) ELA　　　　**(b)** Mathematics

Figure 2.1: Cross-Sectional Relationship between Violent Crime and Achievement

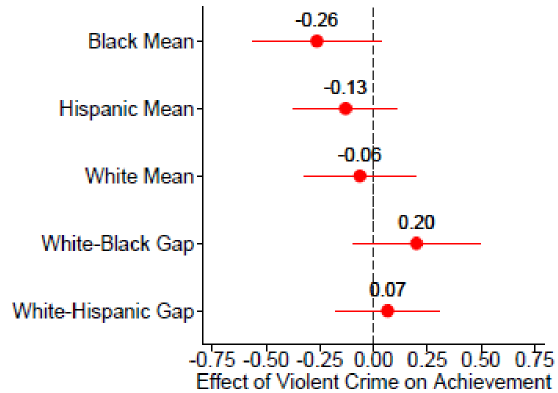


(a) ELA　　　　**(b)** Mathematics

Figure 2.2: OLS and 2SLS Estimates for All Students



(a) ELA



(b) Mathematics

Figure 2.3: 2SLS Estimates by Race

Table 3.1 Pairwise Correlations between District Socioeconomic Status Composite and Other Factors

	rho	pval
White-Black Income V-Gap	0.02	
White-Hispanic Income V-Gap	0.09	***
White-Black Parent Education V-Gap	0.04	*
White-Hispanic Parent Education V-Gap	-0.13	***
Black-White Difference in Exposure to Poverty	-0.12	***
Hispanic-White Difference in Exposure to Poverty	-0.05	**
Proportion Asian in Public Schools	0.40	***
Proportion Hispanic in Public Schools	-0.17	***
Proportion Black in Public Schools	-0.48	***
Average Student-Teacher Ratio	-0.02	
Per Pupil Instructional Expenditures (in $10,000s)	0.28	***
Proportion Attending Charter Schools	-0.11	***
Proportion Novice Teachers	-0.21	***
Proportion Teachers Absent 10+ Days	-0.05	***
Average Teacher Salary	0.35	***
Black/White Student-Teacher Ratio Ratio	-0.01	
Hispanic/White Student-Teacher Ratio Ratio	-0.02	
Black-White Charter Enrollment Difference	0.03	*
Hispanic-White Charter Enrollment Difference	0.05	**
Black-White Novice Teacher Exposure Difference	-0.08	***
Hispanic-White Novice Teacher Exposure Difference	-0.03	
Black-White Chronically Absent Teacher Exposure Difference	-0.04	**
Hispanic-White Chronically Absent Teacher Exposure Difference	0.01	
White-Black Average Teacher Salary Difference	-0.03	
White-Hispanic Average Teacher Salary Difference	0.01	
Black-White Suspension Rate Difference	-0.15	***
Hispanic-White Suspension Rate Difference	0.23	***
Black-White Disability Rate Difference	0.12	***
Hispanic-White Disability Rate Difference	0.52	***
Black-White Grade Retention Rate Difference	0.01	
Hispanic-White Grade Retention Rate Difference	0.01	

***p<=.001; **p<=.01; *p<=.05. Correlations are from bivariate meta-regression models and are weighted by the standard error of the SES composite. Restricted to districts with non-missing white-black or white-Hispanic test score gap in math or ELA

Table 3.2 Relationship between Achievement Gaps and SES Composite (Coefficients on SES Composite Shown)

	White-Black Gaps				White-Hispanic Gaps			
	Math		ELA		Math		ELA	
Model 1: SES Composite Only	0.072	***	0.041	***	0.079	***	0.045	***
	(0.004)		(0.004)		(0.004)		(0.004)	
Model 2: Model 1 + Minority-White Income & Education Gaps	0.065	***	0.034	***	0.089	***	0.063	***
	(0.004)		(0.004)		(0.004)		(0.004)	
Model 3: Model 2 + Racial SES Inequality Saturation	0.098	***	0.069	***	0.081	***	0.050	***
	(0.004)		(0.004)		(0.004)		(0.004)	
Model 4: Model 1 + Segregation	0.069	***	0.038	***	0.093	***	0.068	***
	(0.003)		(0.003)		(0.003)		(0.003)	
Model 5: Model 4 + Racial Composition, PPE, Charter Enrollments	0.071	***	0.056	***	0.077	***	0.065	***
	(0.005)		(0.004)		(0.004)		(0.004)	
Model 6: Model 5 + Class Size, Teacher Quality	0.071	***	0.056	***	0.077	***	0.065	***
	(0.005)		(0.004)		(0.004)		(0.004)	
Model 7: Model 6 + Suspension, Disability and Retention Rates	0.071	***	0.055	***	0.054	***	0.046	***
	(0.004)		(0.004)		(0.004)		(0.004)	
N	2385		2385		3075		3077	

***p<=.001; **p<=.01; *p<=.05; Models are precision weighted meta-regression models. The coefficients shown in the table are coefficients on the SES composite. The other variables included in the models are described below:

Model 1: SES Composite Only

Model 2: Model 1, white-minority income v-gap, white-minority education v-gap

Model 3: Model 2, all racial SES inequality variables, included linearly, as quadratic and and interacted

Model 4: Model 2, white-minority differences in exposure to poverty

Model 6: Model 4, average student-teacher ratio, proportion novice teachers in the average student's school, teacher chronic absent rate (10+ days) in the average student's school, teacher salary in the average student's school, minority/white student-teacher ratio ratio, minority-white novice teacher exposure difference, minority-white chronically absent teacher exposure difference, minority-white average teacher salary difference.

Model 7: Model 5, minority-white suspension rate difference, minority-white disability rate difference, minority-white grade retention rate difference.

Table 3.3: Relationship Average District SES and White-Minority Achievement Gaps

	Math						ELA					
	M1		M2		M3		M1		M2		M3	
White-Black Gap												
Socioeconomic Status Scale	0.053	***	0.065	***	0.053	***	0.043	***	0.051	***	0.044	***
	(0.006)		(0.005)		(0.006)		(0.006)		(0.005)		(0.006)	
White-Minority Income V-Gap	0.080	***	0.078	***	0.079	***	0.076	***	0.074	***	0.075	***
	(0.008)		(0.008)		(0.008)		(0.008)		(0.008)		(0.008)	
White-Minority Parent Education V-Gap	0.199	***	0.201	***	0.200	***	0.254	***	0.255	***	0.254	***
	(0.010)		(0.010)		(0.010)		(0.010)		(0.010)		(0.010)	
White-Minority Income V-Gap*SES	0.031	***			0.023	**	0.021	**			0.014	
	(0.007)				(0.008)		(0.007)				(0.008)	
White-Minority Parental Education V-Gap*SES			0.035	***	0.022	*			0.026	**	0.018	
			(0.009)		(0.010)				(0.009)		(0.010)	
N	2385		2385		2385		2385		2385		2385	
White-Hispanic Gaps												
Socioeconomic Status Scale	0.062	***	0.032	***	0.032	***	0.058	***	0.031	***	0.032	***
	(0.006)		(0.007)		(0.008)		(0.006)		(0.007)		(0.007)	
White-Minority Income V-Gap	0.086	***	0.085	***	0.085	***	0.092	***	0.090	***	0.091	***
	(0.008)		(0.007)		(0.008)		(0.007)		(0.007)		(0.007)	
White-Minority Parent Education V-Gap	0.157	***	0.151	***	0.151	***	0.230	***	0.225	***	0.225	***
	(0.009)		(0.009)		(0.009)		(0.009)		(0.009)		(0.009)	
White-Minority Income V-Gap*SES	0.024	***			0.004		0.012				-0.004	
	(0.007)				(0.008)		(0.007)				(0.007)	
White-Minority Parental Education V-Gap*SES			0.064	***	0.062	***			0.048	***	0.050	***
			(0.009)		(0.009)				(0.008)		(0.009)	
N	3075		3075		3075		3077		3077		3077	

**p<=.01; *p<=.05; Models are precision weighted meta-regression models. The other variables included in the models include: white-minority differences in exposure to poverty, proportion Asian, proportion black, proportion Hispanic, per pupil expenditures (district level), proportion attending charter schools, white-minority charter enrollment difference

Table 3.4: Racial/Ethnic Variation in the Relationship between Achievement and SES

	Math									
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Linear		Quadratic		Linear					
	All Obs		All Obs		Overlap (1st to 99th)		Overlap (5th to 95th)		Overlap (10th to 90th)	
SES Scale	0.305	***	0.246	***	0.260	***	0.204	***	0.064	
	(0.003)		(0.004)		(0.005)		(0.014)		(0.125)	
Black	-0.259	***	-0.230	***	-0.227	***	-0.213	***	0.033	
	(0.009)		(0.009)		(0.011)		(0.017)		(0.110)	
Hispanic	-0.177	***	-0.167	***	-0.182	***	-0.179	***	-0.040	
	(0.006)		(0.006)		(0.006)		(0.009)		(0.068)	
SES*Black	-0.189	***	-0.092	***	-0.102	***	-0.038		0.796	
	(0.005)		(0.010)		(0.017)		(0.053)		(0.410)	
SES*Hispanic	-0.181	***	-0.091	***	-0.099	***	-0.028		0.494	*
	(0.005)		(0.008)		(0.010)		(0.028)		(0.252)	
SES Scale^2			0.059	***						
			(0.003)							
SES^2*Black			-0.048	***						
			(0.004)							
SES^2*Hispanic			-0.040	***						
			(0.004)							
Constant	0.017	***	0.005		0.016	***	-0.001		-0.039	
	(0.003)		(0.003)		(0.003)		(0.004)		(0.033)	
Black = White?	0.000		0.000		0.000		0.476		0.053	
Hispanic = White?	0.000		0.000		0.000		0.330		0.050	
N	16531		16531		11241		5623		1128	

1st to 99th is a data restriction to include SES observations from the 1st percentile of white SES to the 99th percentile of black SES; 5th to 95th and 10th to 90th are comparable.

P-values for tests of equality are based on SES*minority=SES^2*minority=0

*There are 3 observations per district -- white, black and Hispanic observations. Achievement and SES are group specific measures

Table 3.5: Racial/Ethnic Variation in the Relationship between Achievement and SES

	ELA									
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Linear		Quadratic		Linear					
	All Obs		All Obs		Overlap (1st to 99th)		Overlap (5th to 95th)		Overlap (10th to 90th)	
SES Scale	0.292	***	0.217	***	0.220	***	0.166	***	0.100	
	(0.003)		(0.004)		(0.005)		(0.011)		(0.107)	
Black	-0.203	***	-0.165	***	-0.168	***	-0.152	***	0.065	
	(0.007)		(0.008)		(0.009)		(0.014)		(0.094)	
Hispanic	-0.214	***	-0.203	***	-0.214	***	-0.218	***	-0.095	
	(0.005)		(0.005)		(0.005)		(0.008)		(0.059)	
SES*Black	-0.164	***	-0.040	***	-0.050	***	0.047		0.703	*
	(0.004)		(0.008)		(0.015)		(0.044)		(0.352)	
SES*Hispanic	-0.128	***	0.002		0.002		0.059	*	0.557	*
	(0.005)		(0.007)		(0.009)		(0.024)		(0.217)	
SES Scale^2			0.076	***						
			(0.003)							
SES^2*Black			-0.063	***						
			(0.003)							
SES^2*Hispanic			-0.043	***						
			(0.004)							
Constant	0.047	***	0.031	***	0.049	***	0.035	***	0.015	
	(0.002)		(0.002)		(0.002)		(0.003)		(0.028)	
Black = White?	0.000		0.000		0.001		0.286		0.046	
Hispanic = White?	0.000		0.000		0.785		0.014		0.011	
N	16509		16509		11219		5613		1123	

1st to 99th is a data restriction to include SES observations from the 1st percentile of white SES to the 99th percentile of black SES; 5th to 95th and 10th to 90th are comparable.

P-values for tests of equality are based on SES*minority=SES^2*minority=0

*There are 3 observations per district -- white, black and Hispanic observations. Achievement and SES are group specific measures

Table 4.1 Bivariate and Multivariate Model Results for Average Gaps in Counties, Coefficients of Interest Shown

		Counties					
		Segregation Only			Segregation + Controls		
Sample	Measure	beta	se	p<=.05	beta	se	p<=.05
NonEcd-ECD	Difference in School Free Lunch Rates - FRPL/NON FRPL	1.01	0.026	*	0.827	0.028	*
NonEcd-ECD	Difference in Tract Poverty Rates- Poor-NonPoor	2.241	0.059	*	1.719	0.065	*
NonEcd-ECD	Dissimilarity index between districts: FRPL/Non FRPL	0.365	0.02	*	0.507	0.027	*
NonEcd-ECD	Dissimilarity index between schools: FRPL/Non FRPL	0.599	0.017	*	0.499	0.019	*
NonEcd-ECD	Information index between districts: FRPL/Non FRPL	1.064	0.046	*	1.016	0.051	*
NonEcd-ECD	Information index between schools: FRPL/Non FRPL	1.178	0.031	*	0.956	0.034	*
NonEcd-ECD	Isolation index between districts: FRPL/Non FRPL	0.094	0.018	*	0.233	0.031	*
NonEcd-ECD	Isolation index between schools: FRPL/Non FRPL	0.177	0.018	*	0.41	0.03	*
NonEcd-ECD	Relative Diversity index between districts: FRPL/Non FRPL	0.9	0.039	*	0.885	0.043	*
NonEcd-ECD	Relative Diversity index between schools: FRPL/Non FRPL	1.01	0.026	*	0.827	0.028	*
NonEcd-ECD	Residential (between Tract) Segregation-D: Poor-NonPoor	0.922	0.024	*	0.724	0.026	*
NonEcd-ECD	Residential (between Tract) Segregation-H: Poor-NonPoor	2.359	0.056	*	1.875	0.063	*
NonEcd-ECD	Residential (between Tract) Segregation-R: Poor-NonPoor	2.241	0.059	*	1.719	0.065	*
NonEcd-ECD	Residential (between Tract) Segregation-S: Poor-NonPoor	0.632	0.039	*	1.409	0.062	*
White-Black	Difference in School Free Lunch Rates - Black-White	1.099	0.036	*	0.726	0.038	*
White-Black	Difference in Tract Poverty Rates- Black-White	1.742	0.098	*	0.817	0.094	*
White-Black	Dissimilarity index between districts: White/Black	0.198	0.021	*	0.267	0.032	*
White-Black	Dissimilarity index between schools: White/Black	0.376	0.025	*	0.225	0.023	*
White-Black	Exposure index between districts: Black/White	-0.276	0.021	*	-0.532	0.048	*
White-Black	Exposure index between schools: Black/White	-0.303	0.02	*	-0.538	0.04	*
White-Black	Information index between districts: White/Black	0.515	0.04	*	0.45	0.045	*
White-Black	Information index between schools: White/Black	0.67	0.033	*	0.429	0.032	*
White-Black	Isolation index between districts: Black/White	0.192	0.023	*	0.729	0.069	*
White-Black	Isolation index between schools: Black/White	0.224	0.021	*	0.672	0.049	*
White-Black	Relative Diveristy index between schools: White/Black	0.623	0.029	*	0.417	0.028	*
White-Black	Relative Diversity index between districts: White/Black	0.546	0.038	*	0.422	0.037	*
White-Black	Residential (between Tract) Segregation-D: White-Black	0.433	0.035	*	0.193	0.032	*
White-Black	Residential (between Tract) Segregation-H: White-Black	0.83	0.043	*	0.426	0.039	*
White-Black	Residential (between Tract) Segregation-R: White-Black	0.758	0.036	*	0.464	0.034	*
White-Black	Residential (between Tract) Segregation-S: Black-White	0.285	0.026	*	0.563	0.048	*
White-Black	Residential (between Tract) Segregation-X: Black-White	-0.35	0.025	*	-0.502	0.042	*
White-Hispanic	Difference in School Free Lunch Rates - Hispanic-White	1.267	0.042	*	0.855	0.046	*
White-Hispanic	Difference in Tract Poverty Rates- Hispanic-White	2.268	0.136	*	1.077	0.134	*
White-Hispanic	Dissimilarity index between districts: White/Hispanic	0.318	0.027	*	0.268	0.037	*
White-Hispanic	Dissimilarity index between schools: White/Hispanic	0.587	0.03	*	0.388	0.029	*
White-Hispanic	Exposure index between districts: Hispanic/White	-0.317	0.021	*	-0.449	0.048	*
White-Hispanic	Exposure index between schools: Hispanic/White	-0.356	0.021	*	-0.53	0.043	*
White-Hispanic	Information index between districts: White/Hispanic	0.857	0.055	*	0.511	0.059	*
White-Hispanic	Information index between schools: White/Hispanic	1.086	0.042	*	0.754	0.043	*
White-Hispanic	Isolation index between districts: Hispanic/White	0.328	0.024	*	0.698	0.098	*
White-Hispanic	Isolation index between schools: Hispanic/White	0.397	0.023	*	1.023	0.066	*
White-Hispanic	Relative Diversity index between districts: White/Hispanic	0.839	0.05	*	0.448	0.052	*
White-Hispanic	Relative Divserity index between schools: White/Hispanic	0.994	0.035	*	0.683	0.038	*
White-Hispanic	Residential (between Tract) Segregation-D: White-Hispanic	0.49	0.042	*	0.27	0.037	*
White-Hispanic	Residential (between Tract) Segregation-H: White-Hispanic	1.193	0.062	*	0.645	0.06	*
White-Hispanic	Residential (between Tract) Segregation-R: White-Hispanic	1.168	0.051	*	0.629	0.055	*
White-Hispanic	Residential (between Tract) Segregation-S: Hispanic-White	0.408	0.03	*	0.54	0.083	*
White-Hispanic	Residential (between Tract) Segregation-X: Hispanic-White	-0.356	0.025	*	-0.28	0.049	*

Table 4.1 Bivariate and Multivariate Model Results for Average Gap Growth in Counties, Coefficients of Interest Shown

		Counties					
		Segregation Only			Segregation + Controls		
Sample	Measure	beta	se	p<=.05	beta	se	p<=.05
NonEcd-ECD	Difference in School Free Lunch Rates - FRPL/NON FRPL	0.009	0.004	*	0.014	0.004	*
NonEcd-ECD	Difference in Tract Poverty Rates- Poor-NonPoor	0.031	0.008	*	0.049	0.010	*
NonEcd-ECD	Dissimilarity index between districts: FRPL/Non FRPL	0.012	0.002	*	0.012	0.004	*
NonEcd-ECD	Dissimilarity index between schools: FRPL/Non FRPL	0.007	0.002	*	0.010	0.003	*
NonEcd-ECD	Information index between districts: FRPL/Non FRPL	0.024	0.006	*	0.025	0.007	*
NonEcd-ECD	Information index between schools: FRPL/Non FRPL	0.010	0.004	*	0.016	0.005	*
NonEcd-ECD	Isolation index between districts: FRPL/Non FRPL	-0.017	0.002	*	-0.003	0.005	
NonEcd-ECD	Isolation index between schools: FRPL/Non FRPL	-0.016	0.002	*	0.001	0.004	
NonEcd-ECD	Relative Diversity index between districts: FRPL/Non FRPL	0.020	0.005	*	0.021	0.006	*
NonEcd-ECD	Relative Diversity index between schools: FRPL/Non FRPL	0.009	0.004	*	0.014	0.004	*
NonEcd-ECD	Residential (between Tract) Segregation-D: Poor-NonPoor	0.018	0.004	*	0.023	0.004	*
NonEcd-ECD	Residential (between Tract) Segregation-H: Poor-NonPoor	0.040	0.008	*	0.054	0.010	*
NonEcd-ECD	Residential (between Tract) Segregation-R: Poor-NonPoor	0.031	0.008	*	0.049	0.010	*
NonEcd-ECD	Residential (between Tract) Segregation-S: Poor-NonPoor	-0.013	0.005	*	0.042	0.009	*
White-Black	Difference in School Free Lunch Rates - Black-White	0.039	0.005	*	0.038	0.007	*
White-Black	Difference in Tract Poverty Rates- Black-White	0.076	0.013	*	0.068	0.015	*
White-Black	Dissimilarity index between districts: White/Black	0.012	0.003	*	0.017	0.005	*
White-Black	Dissimilarity index between schools: White/Black	0.018	0.003	*	0.015	0.004	*
White-Black	Exposure index between districts: Black/White	-0.003	0.003		-0.029	0.008	*
White-Black	Exposure index between schools: Black/White	-0.003	0.003		-0.026	0.007	*
White-Black	Information index between districts: White/Black	0.025	0.005	*	0.027	0.007	*
White-Black	Information index between schools: White/Black	0.024	0.004	*	0.023	0.005	*
White-Black	Isolation index between districts: Black/White	0.001	0.003		0.043	0.011	*
White-Black	Isolation index between schools: Black/White	0.001	0.003		0.027	0.008	*
White-Black	Relative Diveristy index between schools: White/Black	0.017	0.004	*	0.017	0.005	*
White-Black	Relative Diversity index between districts: White/Black	0.021	0.004	*	0.019	0.006	*
White-Black	Residential (between Tract) Segregation-D: White-Black	0.028	0.004	*	0.023	0.005	*
White-Black	Residential (between Tract) Segregation-H: White-Black	0.033	0.005	*	0.029	0.006	*
White-Black	Residential (between Tract) Segregation-R: White-Black	0.020	0.005	*	0.021	0.006	*
White-Black	Residential (between Tract) Segregation-S: Black-White	0.001	0.003		0.023	0.008	*
White-Black	Residential (between Tract) Segregation-X: Black-White	-0.003	0.003		-0.021	0.007	*
White-Hispanic	Difference in School Free Lunch Rates - Hispanic-White	0.053	0.005	*	0.038	0.007	*
White-Hispanic	Difference in Tract Poverty Rates- Hispanic-White	0.110	0.016	*	0.062	0.020	*
White-Hispanic	Dissimilarity index between districts: White/Hispanic	0.017	0.003	*	0.023	0.005	*
White-Hispanic	Dissimilarity index between schools: White/Hispanic	0.030	0.004	*	0.024	0.004	*
White-Hispanic	Exposure index between districts: Hispanic/White	-0.027	0.003	*	-0.039	0.007	*
White-Hispanic	Exposure index between schools: Hispanic/White	-0.027	0.003	*	-0.035	0.006	*
White-Hispanic	Information index between districts: White/Hispanic	0.045	0.006	*	0.040	0.008	*
White-Hispanic	Information index between schools: White/Hispanic	0.052	0.005	*	0.041	0.007	*
White-Hispanic	Isolation index between districts: Hispanic/White	0.025	0.003	*	0.059	0.013	*
White-Hispanic	Isolation index between schools: Hispanic/White	0.026	0.003	*	0.046	0.010	*
White-Hispanic	Relative Diversity index between districts: White/Hispanic	0.040	0.006	*	0.026	0.007	*
White-Hispanic	Relative Divserity index between schools: White/Hispanic	0.045	0.004	*	0.031	0.006	*
White-Hispanic	Residential (between Tract) Segregation-D: White-Hispanic	0.021	0.005	*	0.012	0.006	*
White-Hispanic	Residential (between Tract) Segregation-H: White-Hispanic	0.056	0.007	*	0.032	0.009	*
White-Hispanic	Residential (between Tract) Segregation-R: White-Hispanic	0.060	0.006	*	0.036	0.008	*
White-Hispanic	Residential (between Tract) Segregation-S: Hispanic-White	0.031	0.003	*	0.046	0.012	*
White-Hispanic	Residential (between Tract) Segregation-X: Hispanic-White	-0.030	0.003	*	-0.030	0.007	*