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Beyond School Police Officers: Racial/Ethnic Disparities in Exposure to a Fuller Range of School Security Personnel

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Beyond School Police Officers: Racial/Ethnic Disparities in Exposure to a Fuller Range of School Security Personnel

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Abstract

Using data from the 2017–18 and 2020–21 Civil Rights Data Collection, we document disparities in exposure to security personnel across US high schools and geographic levels. We distinguish between law enforcement officers (LEOs) and school security guards (SSGs) to capture variation in how security roles are deployed. Results show that Black and Hispanic students experience greater exposure to security personnel than White students. The disparity mainly arises from differences in exposure to SSGs and district and metropolitan variation, although disparities are present across all geographic scales and for law enforcement officers. Our findings suggest that reform should not only focus on officer presence within schools but also structural inequalities in security personnel deployment by type and across districts and regions.

Keywords:

Ethnic and racial disparities, school policing, school security guards, Civil Rights Data Collection, education policy

Beyond School Police Officers: Racial/Ethnic Disparities in Exposure to a Fuller Range of School Security Personnel

Federal funding to promote school safety dates back to the 1960s when amendments to the Omnibus Crime Control and Safe Streets Act established the statutory authority that later shaped the School Violence Prevention Program (SVPP) and the Office of Community Oriented Policing Services (COPS). These provisions encouraged formal partnerships between schools and local law enforcement agencies (Hinton, 2015). Over time, federal legislation and accompanying funding mechanisms appear to have increased state and district interest in the use of school security personnel as a primary strategy to promote school safety, especially in reactive response to the rise in high-profile school shootings in the United States (Fisher & Hennessy, 2016; Kupchik & Bracy, 2009) beginning with the Columbine High School Massacre in 1999. However, given the complex history between law enforcement agencies and communities of color as well as racial disproportionality in the legal system, conceptualizations of school safety that involve the use of law enforcement have raised concerns about raced carceral logics in schools and the implications for the school-to-prison nexus (STPN) (Meiners, 2010). Carceral logics in schools refer to the adoption of surveillance, control, and punishment practices such as zero tolerance policies, surveillance, and policing that mirror the operations of prisons and legal systems, treating students as potential offenders rather than learners (Rudolph, 2023).

Of particular interest for the current study is the racial inequity in exposure to school security personnel, a noted contributor to the STPN (Thurau & Wald, 2009). The police-free schools movement which gained momentum in the wake of the 2020 police killing of George Floyd (Richards, 2020), helped fuel institutional conversations and decisions regarding school safety, including the role that structural factors play in shaping how safety is defined and enforced in schools (e.g., Irwin, Varela, & Peguero, 2022). We argue that racial segregation, racialized poverty, and racial composition of schools are central to these debates because of their influence on which students are seen as needing supervision versus support and thus are central to the current study. As of June 2022, at least 50 school districts serving nearly two million students defunded or reduced funding for their school policing programs (Pendharkar, 2023). Notably, the Chicago Board of Education recently voted to remove police officers from schools, though the schools will still utilize roughly 1,400 school security officers (Franza & Perlman, 2024). Such a decision highlights the need for a broader discussion about the full range of school security personnel, including their distribution and effects (Al Khafaji-King & Rodriguez, 2024).

School security personnel generally include school resource officers (SROs), school police officers (SPOs), and school security guards (SSGs). Because these terms often carry different meanings across districts and in the literature, we briefly clarify our terminology here to prevent ambiguity. While specific localities may use these terms interchangeably, the Civil Rights Data Collection (CRDC) has a nationally consistent definition in the language used when collecting data on school security personnel. Specifically, CRDC identifies SSGs as an individual who guards, patrols, and/or monitors the school premises but is not a sworn law enforcement officer (LEO). CRDC also asks about LEOs, who have arrest authority and can be employed by any entity (e.g., police department, school district, or school). For our purposes, our definition of LEOs encompasses both SROs and SPOs since CRDC does not differentiate between these two types. LEOs provide a well-documented and understood penultimate mediating step in the STPN for students of color, as they have arresting authority over students, and quasi-experimental studies show that exposure to LEOs disproportionately affects the likelihood of arrests for Black students (Pigott et al.,2017; Sorensen et al., 2023).

By contrast, comparable high-quality intervention evidence on school security guards is limited, and the role of SSGs remains less clear. We theorize that SSGs have an important mediating role in the STPN but can have contradictory influences. In one way, SSGs may contribute to the STPN by the enforcement of dress codes, behavior, and regulation of incoming contraband, thereby reinforcing disciplinary structures and carceral logics. Conversely, SSGs may attenuate the STPN by regulating traditionally externally policed activities that enter schools (e.g., when students bring narcotics to school) (Vernon & Curran, 2024) or by, with appropriate training, supporting students' behavioral development in more constructive ways (Forber-Pratt et al., 2023). To date, no rigorous causal evidence speaks to these two competing roles. Qualitative evidence supports the first case (e.g., Mallett, 2015) and correlational evidence supports the latter (e.g., Owens, 2017).

Furthermore, the assignment process of security personnel to schools and districts is an important, yet empirically understudied topic in the extant literature. Existing evidence suggests assignment decisions vary by state, district, and school (Thurau & Wald, 2009). The placement process for SROs and SPOs overlaps in factors that are or should be considered. These include school size, safety and disciplinary incident rates, local needs, and input from school and district administrators (U.S. Department of Justice, Office of Community Oriented Policing Services, 2022). Several states have enacted laws that mandate or structure the presence of school security personnel in school districts. For example, Maryland's Safe to Learn Act of 2018 requires all public schools to have LEOs (Maryland General Assembly, 2018). Texas House Bill 3 of 2023 requires armed LEOs at every school, though districts may apply for exemptions with alternative safety plans (Texas Legislature, 2023). Wisconsin's Act 12 (2023) mandates that schools in the Milwaukee school district (and only this district) with higher rates of disciplinary incidents assign SROs via cost-sharing or partial reimbursement models (Wisconsin Legislature, 2023). SSGs are similarly placed based on comparable metrics, though staffing is usually governed by district-level policy and budget decisions (Sorensen et al., 2023).

Given the different potential influences of school security personnel towards racial inequality in the STPN, assignment processes for law-enforcement officers and security guards, the ongoing rise in high-profile school shootings that have intensified the national focus on school safety, and potential heterogeneity in how these personnel interact with different racial/ethnic student populations, it is essential to understand just how unequally these two types of personnel—LEOs and SSGs—are distributed across schools. For example, if future analysis indicated a robust relationship between Black student's exposure to SSGs and the STPN, this could warrant different policy and practice decisions about the use and placement of SSGs in schools. However, a systematic understanding of where SSGs are located and who is exposed to them is needed first. These personnel play an influential role in shaping students' school experiences, especially for those from historically marginalized groups. Unequal exposure to SSGs may contribute to disparities in discipline, affect students' sense of safety and belonging, and shape family and community trust in schools. For school leaders and policymakers, understanding these patterns is vital to making informed decisions about staffing and resource allocation, and to ensuring that safety efforts do not unintentionally reinforce racial inequities. Then, the availability of descriptive and causal evidence collectively would allow the field to assess whether removing LEOs from schools, while keeping SSGs intact (as in Chicago Public Schools) addresses the larger concern. As such, we seek to answer the descriptive component of the school security personnel story by exploring:

1. What is the magnitude of racial/ethnic disparities in exposure to school security personnel both overall (combining LEOs and SSGs) and disaggregated by officer type?
2. How much of the racial/ethnic disparity in exposure to security personnel is attributable to differences across subnational units (region, division, state/Core Based Statistical Area, district)?

3. To what extent do racial segregation, racial differences in exposure to school poverty, and racial composition predict racial/ethnic disparities in exposure to school security personnel?

Prior studies addressing racial/ethnic inequality in prevalence and exposure to school policing have focused exclusively on LEOs. These studies showed that both prevalence (i.e., where officers are employed) and exposure (i.e., likely frequency of encounters) to officers in schools is patterned by the racial/ethnic composition of the student body. This distinction is especially important in secondary schools, where prevalence captures whether any security personnel are present, while exposure is also sensitive to staffing intensity within schools. Two schools may both report security personnel, yet students are likely to experience different levels of contact when one school employs multiple officers or guards and another employs only one. Accordingly, prevalence is useful for describing where security personnel are located, while exposure better captures the quantity of security personnel students are likely to encounter. For example, using data from the 2013-2014 CRDC, officer prevalence was found to be greatest in schools with the largest shares of Black and Hispanic students (e.g., Lindsay, Lee, & Lloyd, 2018). Between 2013-2014 and 2017-2018, however, the officer prevalence in these schools (i.e., with the most students of color) declined, while prevalence of officers in schools with the fewest students of color held steady for secondary schools and increased for elementary schools (Gleit, 2022). Although these patterns are important, they should be considered in the context of officers' roles. While students in schools with more Black, Latinx, and Native American students tend to have the highest exposure to LEOs, who are more often tasked with punitive roles, students in schools with more white students also encounter LEOs frequently, but in contexts where officers are more often assigned nonpunitive functions (Gleit, 2022). This literature provides evidence of racial disparities in how LEOs are present and used in schools.

Our research addresses some notable gaps in the literature. First, according to CRDC data, there are more full-time employed (FTE) SSGs than LEOs (30,000 FTE SSGs compared to 22,000 FTE SROs). Thus, whether SSGs are unequally distributed by race/ethnicity will help inform the field's understanding of their potential for remediating or exacerbating racial differences in the STPN. Prior literature has focused on the racial/ethnic composition of schools as the primary predictor of prevalence and exposure. However, we argue that broader patterns of racial/ethnic segregation across geographic units mediate exposure to school security personnel. We expect this mediating influence, first, because racial/ethnic segregation is multilayered and varies in severity at different geographical aggregations (Fischer et al., 2004; Jang, 2024; Owens & Reardon, 2016; Reardon et al., 2008). Second, geographical factors influence the distribution of school resources (e.g., school funding is more unequally distributed across states than within (Lee et al., 2022), and access to school resources is mediated by racial/ethnic segregation (Sosina & Weathers, 2019; Weathers & Sosina, 2022). Taken together, our more comprehensive analysis of differential exposure to school security personnel will include SSGs and focus on geographic variation.

Data and Methods

We draw on data from the two most recent waves of the Civil Rights Data Collection (CRDC) – 2017–18 and 2020–21 – administered by the U.S. Department of Education's Office for Civil Rights (OCR), which covers all K–12 public schools nationwide. We limit our analysis to these two cycles, as they include consistent questions on school safety personnel, whereas we exclude the 2015-16 cycle due to known reporting issues that affected data from more than 69,000 schools. In terms of data missingness, around 3% of total observations were missing data related to school safety personnel in our two focal waves, which is most notably due to issues with New York City Public Schools (NYCPS). When NYCPS submitted data to the CRDC in 2017-17, there was a technical submission error causing their school-security staffing data to be marked “force-certified,” meaning the data were accepted despite unresolved missing entries. Because this missingness is concentrated in a single, high enrollment district, we note it explicitly here rather than treating it as diffuse item nonresponse across the national sample. In the 2020–21 wave, approximately 5% of schools were missing data on school-security personnel, and all submissions underwent OCR’s standard data-quality suppression procedures prior to public release (Office for Civil Rights, 2023). Unlike earlier waves, no specific states or districts were singled out for data-quality concerns in 2020–21. However, documentation does note that OCR did apply data quality suppressions in that wave that was either not consistent, had errors, or had signs of poor quality. Nonetheless, none of the current documentation raises concern with the missing data on school security personnel in these waves.

We also use the Common Core of Data (CCD), provided by NCES, specifically school enrollment by racial/ethnic group and free lunch program eligibility. Additionally, these data include the region, division, state, and district where the school is located, which allows us to estimate racial/ethnic differences in exposure to policing at the national and subnational levels. The Common Core of Data (CCD) is a federally mandated, universe-level survey of all public schools and school districts in the United States, collected annually by the National Center for Education Statistics (NCES). CCD collects a wide range of administrative information, including student enrollment counts disaggregated by grade, race/ethnicity, and gender. Because enrollment counts are required for all public schools and districts, these data exhibit minimal missingness, making them highly reliable for analyses of student demographics and cross-state comparisons. Researchers using CCD data can generally treat enrollment counts by race as complete and comparable across schools and years (NCES, 2023). To obtain identifier information on Core Based Statistical Areas (CBSAs), we used the Stanford Education Data Archive (SEDA) for the academic years 2017–18 and 2020–21, which uses the Common Core of Data (CCD) for district- and school-level enrollment counts by race/ethnicity to link to standardized assessment outcomes. We exclude juvenile justice centers (less than 1% of schools), due to high missing data (over 50%) on relevant questions. The final dataset includes about 80,000 schools each year from nearly 13,000 school districts. All analyses are conducted at the school level, aggregating counts and enrollments accordingly.

The key variables for our analyses are the number of FTE school security personnel per 1,000 students within a school. We identified approximately 200 observations in the CRDC with extreme FTE values. To address this, we conservatively winsorized any values for counts of school security personnel per 1,000 students that exceeded three times the 99th percentile.[1]

In our study, we operationalize exposure as the average level of security staffing that students from different racial/ethnic backgrounds encounter, rather than focusing solely on prevalence or encounter frequency. We use this measure because prevalence captures whether a school employs any security personnel, while exposure also reflects staffing intensity in schools that employ multiple guards or officers, a distinction that is especially important for larger secondary schools. To estimate racial/ethnic differences in exposure to school security personnel, we employ a variance decomposition estimator that compares staffing levels between paired groups (Black-White and Hispanic-White) across multiple geographic levels. This method allows us to assess how disparities are distributed spatially, from broader regions to individual schools. Our approach builds on prior applications of this technique in educational research (e.g., Goldhaber, Lavery, & Theobald, 2015). Our estimand represents the average difference in school-level staffing rates between Black (or Hispanic) and White students, expressed per 1,000 students. We decompose these nationwide disparities into components attributable to variation between schools within the same district, between districts within the same CBSA, between CBSAs within the same Census division, and between divisions within the same Census region. By weighting the decomposition using the total number of students in each subgroup enrolled in each geographic unit (for example, in the within district analysis that estimates Black-White exposure gaps, we weight each school level component by the number of Black or White students enrolled in that school), we estimate the relative contribution of schools, districts, CBSAs, divisions, and regions to overall racial and ethnic disparities in disciplinary personnel. This approach clarifies whether disparities are primarily concentrated within individual schools or reflect broader patterns of geographic segregation. Technical details of our estimation strategy are provided in the Supplemental Appendix online.

We focus on the distribution of LEOs and SSGs across high schools because security personnel are more likely to be in high schools, and including elementary schools may attenuate differential exposure; however, our supplemental results from Table A1 also include combined elementary, middle, and high schools. For geographic decomposition, we emphasize CBSAs over metropolitan statistical areas (MSAs) and states. Relative to MSAs alone, the CBSA includes other more rural geographies (urban cores with populations of 10,000 to 49,999) and more comprehensive coverage of the US (Office of Management and Budget, 2018; e.g., 95% of the US population for CBSAs compared to 86% for MSAs). Relative to states, the CBSA is a geographic entity that can encompass multiple state boundaries as measured by commuting ties and, because it includes MSAs as jurisdictional boundaries, can act as a centralized funding agency for SRO staffing. We provide supplemental results that decompose variation into the within state (as opposed to within CBSA) component, which can be found in Supplemental Appendix Tables A2 and A3.

Our predictor variables for research question three include: racial segregation, racial composition, and racial differences in exposure to school poverty. Racial segregation captures the degree of racial separation in school enrollment within CBSAs, a necessary but not sufficient component for unequal exposure to SSGs. [2] Racial composition measures the proportion of non-White students, testing whether SSG deployment reflects racial threat dynamics or implicit biases that associate higher concentrations of students of color with greater need for surveillance and control (Eitle, et al., 2002). Racial differences in exposure to school poverty account for the unequal concentration of students in high-poverty schools, which often face greater surveillance and security enforcement and represent the largest documented driver of racial achievement differences (Reardon, 2016; Reardon et al., 2024).[3]

Results

RQ1: Magnitude of Racial/Ethnic Disparities in Exposure to School Security Personnel

Analysis of differential exposure to school security personnel reveals substantial Black–White and Hispanic–White disparities in both 2017–18 and 2020–21. As shown in Table 1, Black students encountered 1.16 more school security personnel (SSGs and LEOs combined) per 1,000 students than White students in 2017–18. This gap narrowed slightly to 1.02 per 1,000 students in 2020–21, though this decline was not statistically significant ($p = .110$), and the 2021 gap itself remains significantly different from zero ($p < .001$), underscoring persistent inequality. Hispanic White disparities follow a similar pattern but are smaller in magnitude. In 2017–18, Hispanic students encountered 0.79 more security personnel per 1,000 students than White students, declining to 0.66 in 2020–21 ($p = .04$ for the change between years), a gap that nonetheless remains significantly different from zero in 2020–21 ($p < .001$).

These disparities were driven primarily by exposure to school security guards (SSGs). In 2017–18, the overall Black White gap in exposure to school security personnel at the high school level was 1.16 personnel per 1,000 students. Of this total, 0.97 personnel per 1,000 were SSGs and 0.17 were law enforcement officers (LEOs). The SSG gap is large relative to the distribution of SSG exposure equal to about 0.87 times the mean level of SSG exposure (1.11 personnel per 1,000 students, SD 2.15) and 0.45 standard deviation units, whereas the

LEO exposure gap is much smaller at 0.17 personnel per 1,000 students, or about 0.26 standard deviation units. Hispanic-White disparities are entirely attributable to SSG exposure, with SSG gaps of 0.75 in 2018 and 0.71 in 2021. Conversely, LEO exposure gaps for Hispanic students were no different from zero in 2018 and slightly negative in 2021 (p = .001).

<Table 1 Here>

RQ2: How Differences Across Subnational Units Contribute to Racial/Ethnic Disparities

A geographic decomposition reveals that Black–White disparities emerge across multiple spatial scales, with the most pronounced source of inequality occurring between districts within CBSAs. The between-district/within-CBSA component accounts for 0.94 FTE per 1,000 students in 2017–18 and 0.83 in 2020–21, equivalent to roughly 80 percent of the total gap in each year. Variation between CBSAs within divisions explains a smaller portion of the gap (0.30 in 2017–18 and 0.26 in 2020–21), and differences between schools within districts are smaller still (0.26 and 0.24). These findings indicate that where students live and attend school, particularly their district within their metropolitan area, plays a powerful role in shaping exposure to school security personnel.

Hispanic–White disparities display a more evenly distributed geographic pattern. In 2017–18, between-CBSA and between-district components were of similar magnitude (0.48 and 0.49), both much larger than the between-school component (0.105). This pattern persisted in 2020–21, with between-CBSA (0.442) and between-district (0.372) components again representing the largest sources of inequality. Although the between-district component declined over time, the change was not statistically significant (p = .247), and the gap remained significantly different from zero ($p < .001$). The more even geographic distribution of the Hispanic–White gap suggests that broader, state-level factors, such as demographic composition, political climate, or funding regimes, may play a larger role than localized segregation alone.

Supplemental analyses using alternative samples and geographic units show that these patterns are robust. Supplemental Appendix Tables A1-A3 report results for all schools using CBSAs (A1), high schools using states instead of CBSAs as the geographic unit (A2), and all schools using states (A3). The overall patterns are quite consistent across these specifications: differential exposure to SSGs continues to drive racial disparities, within-state variation remains the dominant source of inequality (similar to within-CBSA exposure), and Hispanic-White gaps are consistently smaller and more evenly distributed across space. The key distinction is that overall exposure levels in the all-schools sample are about 60% lower than in the high school sample, an expected result given that many elementary schools do not report the presence of any school security personnel.

Table 1 shows that the between-region component of the Black–White and Hispanic–White school security-personnel gaps is negative (–0.356 and –0.295, respectively). A negative residual at the four-region scale indicates that Census regions enrolling disproportionately large shares of Black and Hispanic high-schoolers have lower average staffing levels. Figure 1 illustrates this pattern by plotting each region's mean number of officers per 1,000 students against its share of the national Black (Panel A) or Hispanic (Panel B) student population, revealing a clear downward slope: regions with larger minority shares staff fewer security personnel. These four regions also correspond to clusters of states with similar, state-driven funding regimes. For example, Southern (and, for Hispanic students, Western) states together enroll over 40 percent of Black and Hispanic high-schoolers yet allocate significantly fewer resources per pupil (Lee et al., 2022). These broader spending disparities appear to extend to the deployment of security personnel. Because these regions, which have lower per-pupil school funding (Lee et al., 2022), enroll the majority of Black and Hispanic students, the between-region residual pulls down the overall exposure gap. However, there are positive exposure gaps on net (i.e., the overall gap) and these gaps remain at every other finer spatial level—division, CBSA, and district--meaning that inter-regional funding imbalances only partially offset more localized disparities.

These geographic patterns carry important implications. First, the fact that within-CBSA variation accounts for the largest share of racial disparities indicates that local policy decisions, particularly those made by individual districts, alongside between-district segregation, play a central role in producing unequal exposure to school security personnel. Disparities therefore reflect not only state policy or regional crime patterns but also district-level choices about how security staff are allocated across schools serving more Black and Hispanic students. Second, the negative between-region component for both groups shows that regions enrolling the highest concentrations of students of color employ fewer security personnel overall, yet racial inequality in exposure persists within those same regions. This creates a paradox in which regions serving more students of color rely less on security staff on average, but within those regions, students of color remain disproportionately surveilled.

<Figure 1 Here>

RQ 3: Predictors of Racial/Ethnic Disparities: Segregation, School Poverty, and Racial Composition

Finally, given the result that within-CBSA inequality is by far the largest source of differential exposure, we emphasize that CBSAs – and metropolitan areas specifically – vary considerably in their level of inequality within this unit. Thus, to explore the factors driving this variation, we estimate CBSA-specific gaps using the same framework as above and plot those below, illustrating the important role of racial segregation as a predictor of exposure.

<Figure 2 Here>

Figure 2 displays scatter plots capturing bivariate associations between CBSA-specific Black-White and Hispanic-White gaps in SSG prevalence and three potential predictors of exposure: racial segregation, racial composition, and racial differences in exposure to school poverty. While both racial segregation and differences in exposure to school poverty show positive bivariate associations with racial differences in SSG exposure, multivariate regression results reveal that racial segregation is the strongest and only significant predictor of between-CBSA variation in SSG exposure. Additionally, Appendix Figure A1 demonstrates that racial disparities in LEO exposure are not significantly explained by any of these three predictors. Taken together, these results suggest the following: (1) racial disparities in SSG exposure are fundamentally associated with structural segregation rather than school demographics or resource differences, (2) SSG deployment patterns operate independently of racial composition or poverty concentration once segregation is accounted for, and (3) LEO placement follows entirely different mechanisms that are not explained by these structural factors.

Discussion

Our findings reveal that Black-White and Hispanic-White disparities in exposure to high school security personnel are large and geographically patterned. Black-White disparities in exposure to high school security personnel are larger in magnitude compared to Hispanic-White disparities and primarily driven by disparities in exposure to SSGs. This pattern exists at nearly all spatial scales. Hispanic-White disparities in exposure to school security personnel are smaller in magnitude but also driven by disparities in exposure to SSGs. A key contrast is the more uniform distribution of Hispanic-White inequality across geographic scales.

These findings suggest that districts removing LEOs in response to the police-free schools movement (e.g., Chicago Public Schools) may still leave Black (primarily) and Hispanic students disproportionately more exposed to school security personnel (specifically, SSGs) than their white peers. One possibility is that some districts may be reallocating SSGs as substitutes for LEOs, which would allow surveillance practices to persist even when sworn officers are removed. For policymakers, this means that addressing racial disparities in school security cannot rely solely on state-level reforms or blanket reductions in security personnel. Instead, targeted efforts are needed to understand and reshape district-level practices, particularly in urban areas where within-metropolitan disparities are most pronounced. It also underscores the importance of examining how school security decisions intersect with broader issues of school funding, racial segregation, and poverty concentration. These patterns suggest that without addressing the local mechanisms that produce these disparities, such as funding formulas and policies, staffing discretion, or disciplinary policy, inequality in student experiences of school surveillance will likely persist even in the face of broader reforms.

Furthermore, given the substantial inequality in exposure to SSGs for Black and Hispanic students in our study, careful consideration of the roles and practices of SSGs is warranted, particularly if they are increasingly being used in place of LEOs. The intersections of multiple marginalized identities in the student population, further support the need for similar analyses of inequality by socioeconomic status, ELL status, special education status, and gender, as well as empirical evidence on the causal effect of SSGs (not just LEOs) on student outcomes. Such evidence will be essential to better understand their role in remediating or exacerbating exposure to the STPN and, if negative impacts are identified, whether policy and advocacy efforts should extend to limiting their presence as well.

Endnotes

[1] Given imperfect accounting practices at the local level and auditing practices at the federal level, some expectation of measurement error and outlier reporting is to be expected. Winsorizing a small number of extreme values is consistent with common practice in federal administrative and education finance research. Though, education finance data are often winsorized more aggressively (e.g., 1.5 times the 95th percentile) than the approach we adopt in the current study. Thus, we have no reason to believe the winsorized staffing values are erroneous.

[2] We draw on segregation measures from the Stanford Education Data Archive (SEDA), which computes racial segregation using Theil's information index. This index reflects the weighted mean deviation of each school's racial composition from the CBSA-wide racial composition. Values range from 0 (complete integration) to 1 (complete segregation).

[3] Racial differences in exposure to school poverty was measured using the share of students eligible for free or reduced-price lunch (FRPL), and computing group-specific exposure as the average FRPL rate experienced by students of each racial/ethnic group within a CBSA.

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Tables

Table 1. Geographic Decomposition of Exposure to School Security Personnel: High School Students and CBSA

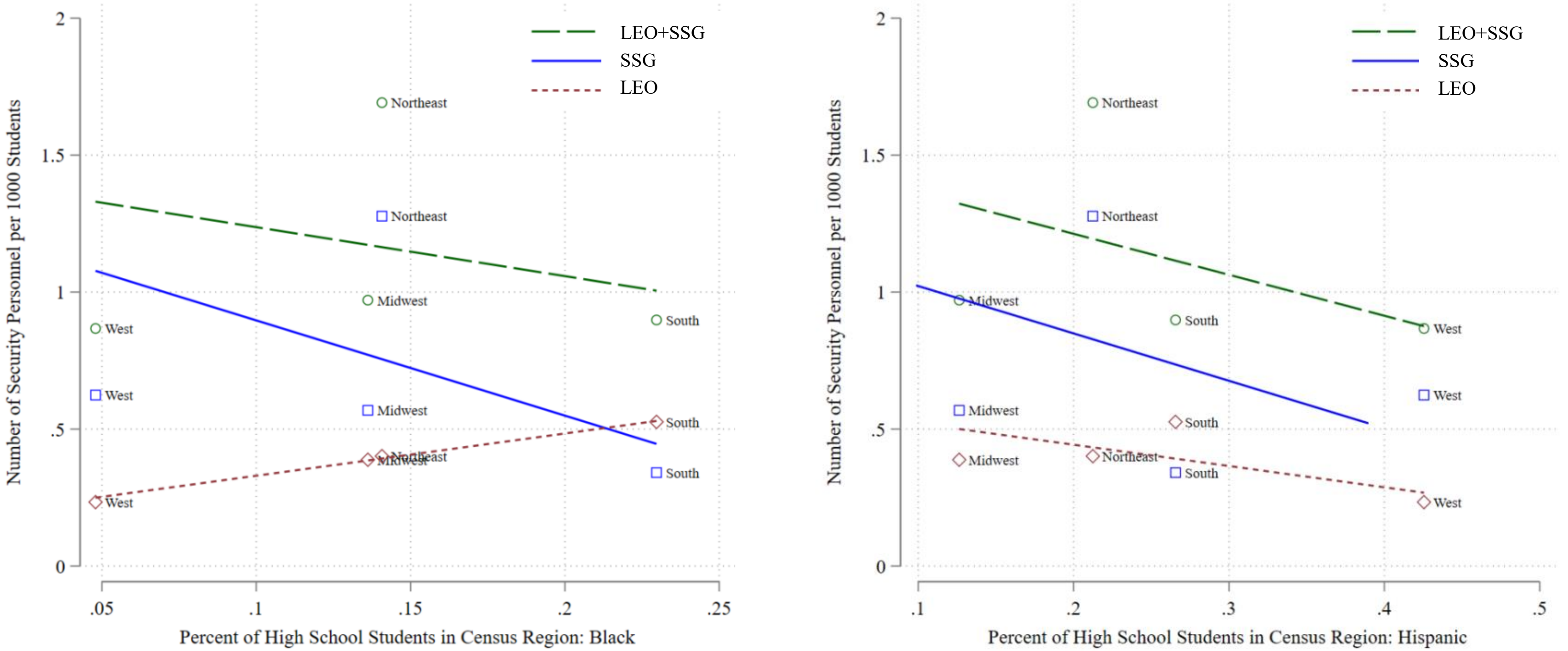
Black vs White Exposure					
2018 Gap Decomposition			2021 Gap Decomposition		
School Security Personnel	School Security Guards	Law Enforcement Officers	School Security Personnel	School Security Guards	Law Enforcement Officers
Overall Gap (USA)					
1.163	0.974	0.172	1.021	0.823	0.179
(0.000)	(0.000)	(0.000)	(0.110; 0.000)	(0.035; 0.000)	(0.863; 0.000)
Within Region Between Division					
0.014	0.034	-0.019	0.033	0.041	-0.009
(0.934)	(0.789)	(0.858)	(0.937; 0.845)	(0.969; 0.761)	(0.940; 0.927)
Within Division Between CBSA					
0.303	0.294	0.010	0.262	0.256	0.005
(0.031)	(0.033)	(0.808)	(0.845; 0.090)	(0.847; 0.080)	(0.952; 0.937)
Within CBSA Between District					
0.944	0.826	0.103	0.832	0.738	0.077
(0.000)	(0.000)	(0.002)	(0.389; 0.000)	(0.458; 0.000)	(0.657; 0.124)
Within District Between Schools					
0.258	0.183	0.069	0.243	0.146	0.090
(0.000)	(0.000)	(0.000)	(0.674; 0.000)	(0.197; 0.000)	(0.200; 0.000)
Between Region					
-0.356	-0.363	0.009	-0.349	-0.358	0.016
Hispanic vs White Exposure					
Overall Gap (USA)					
0.792	0.749	0.026	0.656	0.712	-0.055
(0.000)	(0.000)	(0.158)	(0.040; 0.000)	(0.511; 0.000)	(0.001; 0.000)
Within Region Between Division					
0.015	0.021	-0.010	0.024	0.039	-0.014
(0.910)	(0.835)	(0.908)	(0.963; 0.861)	(0.910; 0.733)	(0.972; 0.845)
Within Division Between CBSA					
0.476	0.484	-0.010	0.442	0.435	0.006
(0.002)	(0.001)	(0.797)	(0.879; 0.007)	(0.819; 0.006)	(0.846; 0.933)

Within CBSA Between District					
0.491	0.412	0.063	0.372	0.354	0.015
(0.000)	(0.000)	(0.052)	(0.247; 0.000)	(0.555; 0.000)	(0.261; 0.592)
Within District Between Schools					
0.105	0.073	0.030	0.083	0.057	0.025
(0.000)	(0.000)	(0.000)	(0.326; 0.000)	(0.339; 0.000)	(0.675; 0.000)
Between Region					
-0.295	-0.241	-0.047	-0.265	-0.173	-0.087

Notes: Gap estimates are based on regression estimates from Equation (1). P-values for the 2018 gap composition are based on the test of whether the gap is different from zero. For 2021, there are two p-values. The first p-value for the 2021 gap composition is based on the test of whether the 2021 gap is different from the 2018 gap, and the second p-value reflects the test of whether the 2021 gap is statistically different from zero. These estimates and, specifically, tests for differences in exposure gaps between 2018 and 2021 survey years are from regression equations from Online Appendix Equation 1. The between-region component of the gap is the residual of the overall gap minus the sum of the gaps at each geographic scale and is not estimated.

Figures

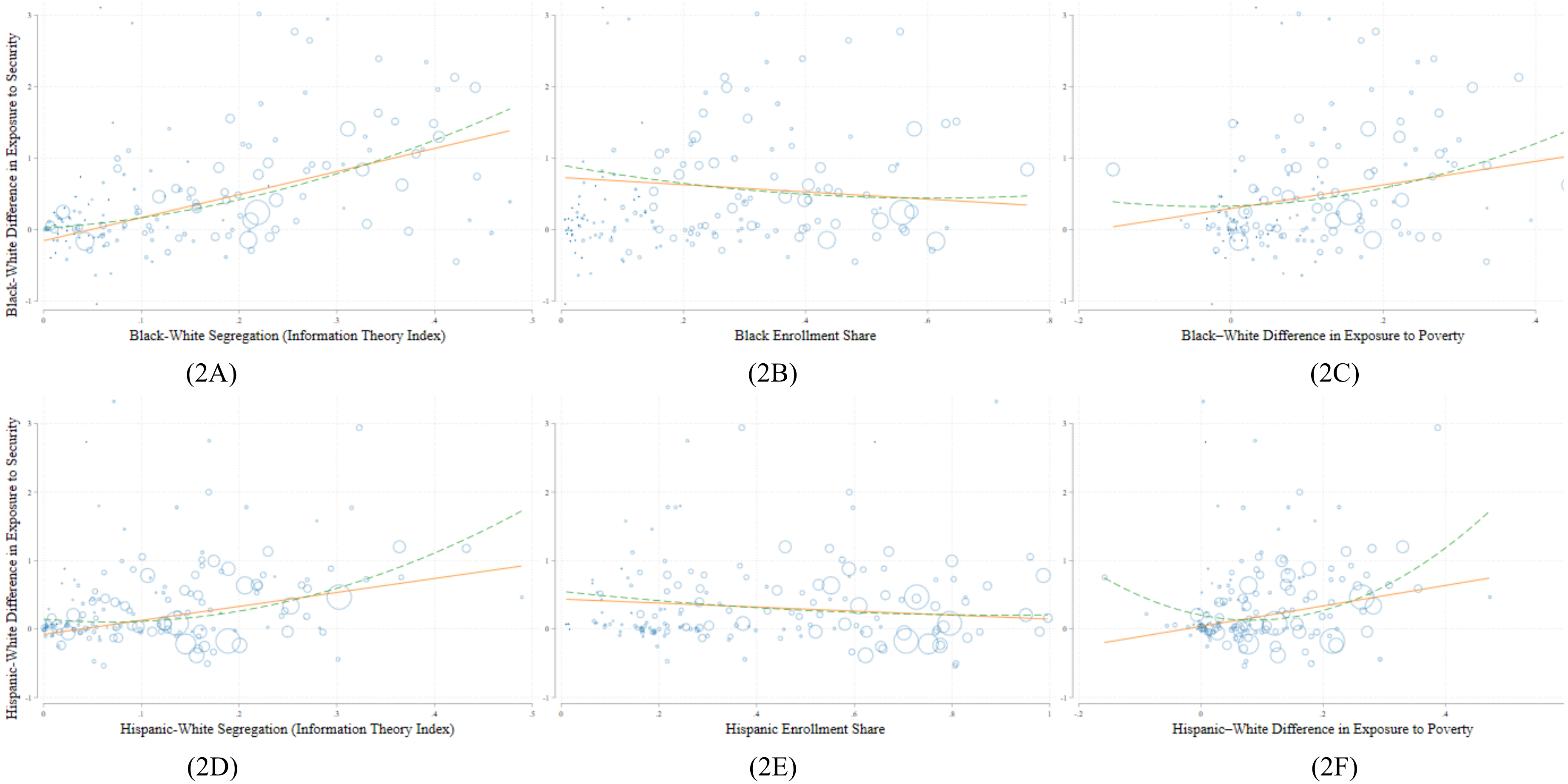
Figure 1. US Census Region Security Personnel by Percent of Census Region that is Black or Hispanic, 2017-18 School Year, High School Students



(1A) (1B)

Note: Figure plots the US Census Region (N=4 regions) average number of security personnel, SSGs, and LEOs per 1000 students as a function of the percent of high school students in the region that are Black or Hispanic (Panels 1A and 1B, respectively; e.g., $\frac{Black_r}{\Sigma Black_r}$). Data restricted to the 2017-18 academic year and high school students. Linear line of best fit is weighted by the percent of high school students in the region that are Black or Hispanic.

Figure 2. CBSA-Specific Gaps in Exposure to SSGs and Racial Segregation



Note: Note: Figure plots the bivariate associations between Black-White and Hispanic-White differences in exposure to SSGs (Panels 2A-2C and 2D-2F, respectively) and three predictors of exposure (racial segregation, racial proportion, and racial difference in exposure to school poverty). Linear (solid) and quadratic (dashed) lines of best fit are weighted by the Black or Hispanic student share.

Online Appendix

Analytical Strategies

Estimating Differences in Exposure to School Security Personnel

Our primary aim is to decompose differences in racial/ethnic exposure to school security personnel at different levels of aggregation. We estimate racial/ethnic differences in exposure to school security personnel using the following equation:

$$Personnel_{lgu} = \beta_{gu} \times group_{lgu} + \delta_u + \varepsilon_{lgu} \qquad (1)$$

Where $Personnel_{lgu}$ indicates the number of FTE school security personnel per 1,000 students in the lower level of aggregation l (e.g., schools) for paired group g (Black-White and Hispanic-White) nested within the upper level of aggregation u (e.g., districts). Because we have counts of data at the l level, in practice to estimate this equation, we stack the data so that each unit l is repeated twice, with the variable enrollment for the group g differentiating each unit l. Then, an indicator variable representing the group is created (i.e., $group_{lgu}$), and the regression is estimated with analytic weights using the enrollment. β_{gu} represents the estimated pairwise group difference g in security personnel per 1,000 students within the upper level geographic unit u , weighted by the enrollment of group g at lower level l. Adjusting for fixed effects at the next higher geographic level restricts the variation to within upper geographic units. In practice, the estimand from this equation is the average group difference in exposure to $Personnel_{lgu}$. For the total gap across the U.S., we omit any fixed effect δ_u; for any other subnational level we include the fixed effect δ_u at the upper level of aggregation u (e.g., to calculate the within CBSA average exposure gap, we include an CBSA fixed effect using enrollment counts at the district l level). ε_{lgu} is the error term adjusted for heteroskedasticity. We estimate $Personnel_{lgu}$ for total security personnel, as well as school security guards and school law enforcement officers, separately. To facilitate tests of whether the 2017-18 and 2020-21 gaps are different, the estimation equation can be modified to be:

$$Personnel_{lgut} = \beta_{gut}(group_{lgut} + group_{lgu} \times yr2021_t) + \delta_{ut} + \varepsilon_{lgut} \qquad (2)$$

In this equation, we now index time with a *t* and modify the fixed effect δ_{ut} so that it is the interaction of units and time. This interaction ensures that the sum of coefficients $\beta_{\widehat{gut=2018}}$and $\beta_{\widehat{gut=2021}}$ from Equation (2) is equal $\widehat{\beta_{gu}}$ from Equation (1) if estimated just for the 2020-21 academic year. In practice, we estimate the interacted equation to obtain both the 2017-18 effect and, via the linear combination of the main 2017-18 and 2020-21 effects, the 2020-21 effect. Then, the test of whether 2020-21 is different from 2017-18 is obtained directly from the regression. Finally, we conduct the post-estimation test of whether the 2020-21 coefficient is different from zero by taking the linear combination of the 2017-18 and 2020-21 coefficients, applying the delta method to obtain a standard error and p-value.

Decomposing Differences in Exposure to School Security Personnel

The decomposition of nationwide differences in exposure to school security personnel is due to a disproportionate concentration of each racial/ethnic subgroup in particular subnational levels that assign differential numbers of school security personnel. To conduct this decomposition, we take the total gap, designated $\text{Dif}_{(US|SC)}$, and parse it into five components: (1) between school, within district, (2) between district, within CBSA (or state), (3) between CBSA (or state), within U.S. Census division, (4) between division, within U.S. Census region, and (5) between region, within nation. Algebraically, this decomposition takes the form:

$$
\begin{aligned}
\mathrm{Dif}_{US|sc} = {} & \mathrm{Dif}_{(5)US|re} \\
& + \sum_{sd} \frac{I_{re} n_{re}}{I_{US} n_{US}} \mathrm{Dif}_{(4)re|div} \\
& + \sum_{re} \frac{I_{div} n_{div}}{I_{US} n_{US}} \mathrm{Dif}_{(3)div|cbsa} \\
& + \sum_{st} \frac{I_{cbsa} n_{cbsa}}{I_{US} n_{US}} \mathrm{Dif}_{(2)cbsa|di} \\
& + \sum_{di} \frac{I_{di} n_{di}}{I_{US} n_{US}} \mathrm{Dif}_{(1)di|sc}
\end{aligned}
$$

(2)

Where $\mathrm{Dif}_{(US|sc)}$ is the average nationwide difference in exposure to school security personnel based on school level data. $\mathrm{Dif}_{(us|re)}$ is the between region within nation difference in exposure. Then, if students from the target subgroup (e.g., Black) are disproportionately concentrated in regions with more school security personnel (and the opposite for the reference group, e.g., White), this component will be large. The second right-side term is a weighted sum of within region differences in exposure to school security personnel based on division-level data ($\mathrm{Dif}_{(re|div)}$). n_{re} and n_{US} indicate enrollment counts at the region and nation levels, respectively; and I_{re} and I_{US} indicate the share of students in the target subgroup at the region and nation levels, respectively, where $I = 2\pi(1-\pi)$ and π is the proportion of students in the region that belong to the target subgroup.[1] Thus, weights are proportional to the size of the region $\frac{n_{re}}{n_{US}}$ and to the share of the target subgroup in the region $\frac{I_{re}}{I_{US}}$. Then, larger and more diverse regions, as well as those with larger within-region differences contribute more to the nationwide difference in exposure to school security personnel.

We follow a similar approach for decomposing within region differences into between US Census division components, within division components into between CBSA components[2], within CBSA differences into between district components, and within district differences into between school components. In practice, we estimate components (1) through (4) using a series of fixed effects regressions as described in Equation (1) where the fixed effect is specified for the "within" component of interest and the "between" component are data aggregated to that level – e.g., for the within CBSA component we include an CBSA fixed effect and use district level data. The remaining between-region component (5) is the residual from this decomposition; that is, it is the remaining piece of the total gap $\text{Dif}_{(US|sc)}$ after subtracting out the components (1) through (4).

Endnotes

[1] Since π is a proportion, its variance is $\pi(1-\pi)$. This multiplicative factor is the "fixed effect weight" in a fixed effects regression. Put differently, the formula is the mathematical expression of the fixed effects regression.

[2] Separately, we replace CBSAs with states and replicate the decomposition. Because CBSAs cross state lines and can define their own municipal boundaries for funding resource officers, we choose to focus on CBSAs as the focal geography and report state-level decompositions in the appendix.

Table A1. Geographic Decomposition of Exposure to School Security Personnel: All Students and CBSA

Black vs White Exposure					
2018 Gap Decomposition			2021 Gap Decomposition		
School Security Personnel	School Security Guards	Law Enforcement Officers	School Security Personnel	School Security Guards	Law Enforcement Officers
Overall Gap (USA)					
0.679	0.611	0.060	0.642	0.581	0.054
(0.000)	(0.000)	(0.000)	(0.286; 0.000)	(0.279; 0.000)	(0.695; 0.000)
Within Region Between Division					
0.006	0.023	-0.016	0.024	0.028	-0.004
(0.970)	(0.782)	(0.864)	(0.928; 0.869)	(0.969; 0.749)	(0.925; 0.968)
Within Division Between CBSA					
0.178	0.182	-0.007	0.136	0.179	-0.043
(0.040)	(0.022)	(0.829)	(0.744; 0.144)	(0.980; 0.042)	(0.587; 0.449)
Within CBSA Between District					
0.490	0.485	0.004	0.445	0.465	-0.027
(0.000)	(0.000)	(0.878)	(0.598; 0.000)	(0.803; 0.000)	(0.521; 0.503)
Within District Between Schools					
0.171	0.125	0.043	0.189	0.107	0.080
(0.000)	(0.000)	(0.000)	(0.331; 0.000)	(0.213; 0.000)	(0.000; 0.000)
Between Region					
-0.166	-0.204	0.036	-0.152	-0.198	0.048
Hispanic vs White Exposure					
Overall Gap (USA)					
0.422	0.427	-0.028	0.351	0.448	-0.094
(0.000)	(0.000)	(0.003)	(0.011; 0.000)	(0.328; 0.000)	(0.000; 0.000)
Within Region Between Division					
0.023	0.020	-0.005	0.011	0.032	-0.021
(0.842)	(0.792)	(0.945)	(0.942; 0.927)	(0.914; 0.695)	(0.872; 0.765)
Within Division Between CBSA					
0.250	0.269	-0.023	0.245	0.262	-0.015
(0.006)	(0.001)	(0.443)	(0.969; 0.011)	(0.956; 0.006)	(0.917; 0.823)
Within CBSA Between District					

0.298	0.273	0.016	0.227	0.242	-0.017
(0.000)	(0.000)	(0.671)	(0.388; 0.000)	(0.627; 0.000)	(0.545; 0.667)
Within District Between Schools					
0.034	0.021	0.010	0.045	0.024	0.021
(0.009)	(0.007)	(0.127)	(0.509; 0.000)	(0.731; 0.002)	(0.174; 0.000)
Between Region					
-0.183	-0.156	-0.026	-0.177	-0.112	-0.062

Notes: Gap estimates are based on regression estimates from Equation (1). P-values for the 2018 gap composition are based on the test of whether the gap is different from zero. For 2021, there are two p-values. The first p-value for the 2021 gap composition is based on the test of whether the 2021 gap is different from the 2018 gap, and the second p-value reflects the test of whether the 2021 gap is statistically different from zero. These estimates and, specifically, tests for differences in exposure gaps between 2018 and 2021 survey years are from regression equations from Online Appendix Equation 1. The between-region component of the gap is the residual of the overall gap minus the sum of the gaps at each geographic scale and is not estimated.

Table A2. Geographic Decomposition of Exposure to School Security Personnel: High School Students and State

Black vs White Exposure

2018 Gap Decomposition			2021 Gap Decomposition		
School Security Personnel	School Security Guards	Law Enforcement Officers	School Security Personnel	School Security Guards	Law Enforcement Officers
Overall Gap (USA)					
1.175	0.983	0.177	1.165	0.809	0.329
(0.000)	(0.000)	(0.000)	(0.908; 0.000)	(0.011; 0.000)	(0.000; 0.000)
Within Region Between Division					
0.017	0.038	-0.021	0.05	0.047	0.003
(0.916)	(0.757)	(0.841)	(0.895; 0.787)	(0.963; 0.713)	(0.879; 0.981)
Within Division Between State					
0.104	0.095	0.009	0.153	0.119	0.032
(0.562)	(0.580)	(0.909)	(0.867; 0.508)	(0.925; 0.495)	(0.890; 0.822)
Within State Between District					
1.093	0.983	0.097	0.941	0.774	0.148
(0.000)	(0.000)	(0.008)	(0.305; 0.000)	(0.223; 0.000)	(0.717; 0.278)
Within District Between Schools					
0.248	0.176	0.067	0.304	0.139	0.155
(0.000)	(0.000)	(0.000)	(0.129; 0.000)	(0.175; 0.000)	(0.000; 0.000)
Between Region					
-0.287	-0.309	0.025	-0.283	-0.270	-0.009

Hispanic vs White Exposure

2018 Gap Decomposition			2021 Gap Decomposition		
Overall Gap (USA)					
0.811	0.777	0.018	0.747	0.716	0.028
(0.000)	(0.000)	(0.314)	(0.314; 0.000)	(0.271; 0.000)	(0.673; 0.089)
Within Region Between Division					
0.009	0.024	-0.019	0.029	0.044	-0.014
(0.946)	(0.812)	(0.815)	(0.917; 0.851)	(0.893; 0.678)	(0.970; 0.879)
Within Division Between State					
0.264	0.279	-0.017	0.262	0.261	-0.002
(0.131)	(0.090)	(0.785)	(0.993; 0.232)	(0.940; 0.122)	(0.918; 0.985)

Within State Between District					
0.682	0.608	0.060	0.590	0.462	0.126
(0.000)	(0.000)	(0.069)	(0.463; 0.000)	(0.329; 0.000)	(0.630; 0.344)
Within District Between Schools					
0.101	0.070	0.029	0.110	0.054	0.054
(0.000)	(0.000)	(0.000)	(0.667; 0.000)	(0.316; 0.000)	(0.054; 0.000)
Between Region					
-0.245	-0.204	-0.035	-0.244	-0.105	-0.136

Notes: Gap estimates are based on regression estimates from Equation (1). P-values for the 2018 gap composition are based on the test of whether the gap is different from zero. For 2021, there are two p-values. The first p-value for the 2021 gap composition is based on the test of whether the 2021 gap is different from the 2018 gap, and the second p-value reflects the test of whether the 2021 gap is statistically different from zero. These estimates and, specifically, tests for differences in exposure gaps between 2018 and 2021 survey years are from regression equations from Online Appendix Equation 1. The between-region component of the gap is the residual of the overall gap minus the sum of the gaps at each geographic scale and is not estimated.

Table A3. Geographic Decomposition of Exposure to School Security Personnel: All Students and State

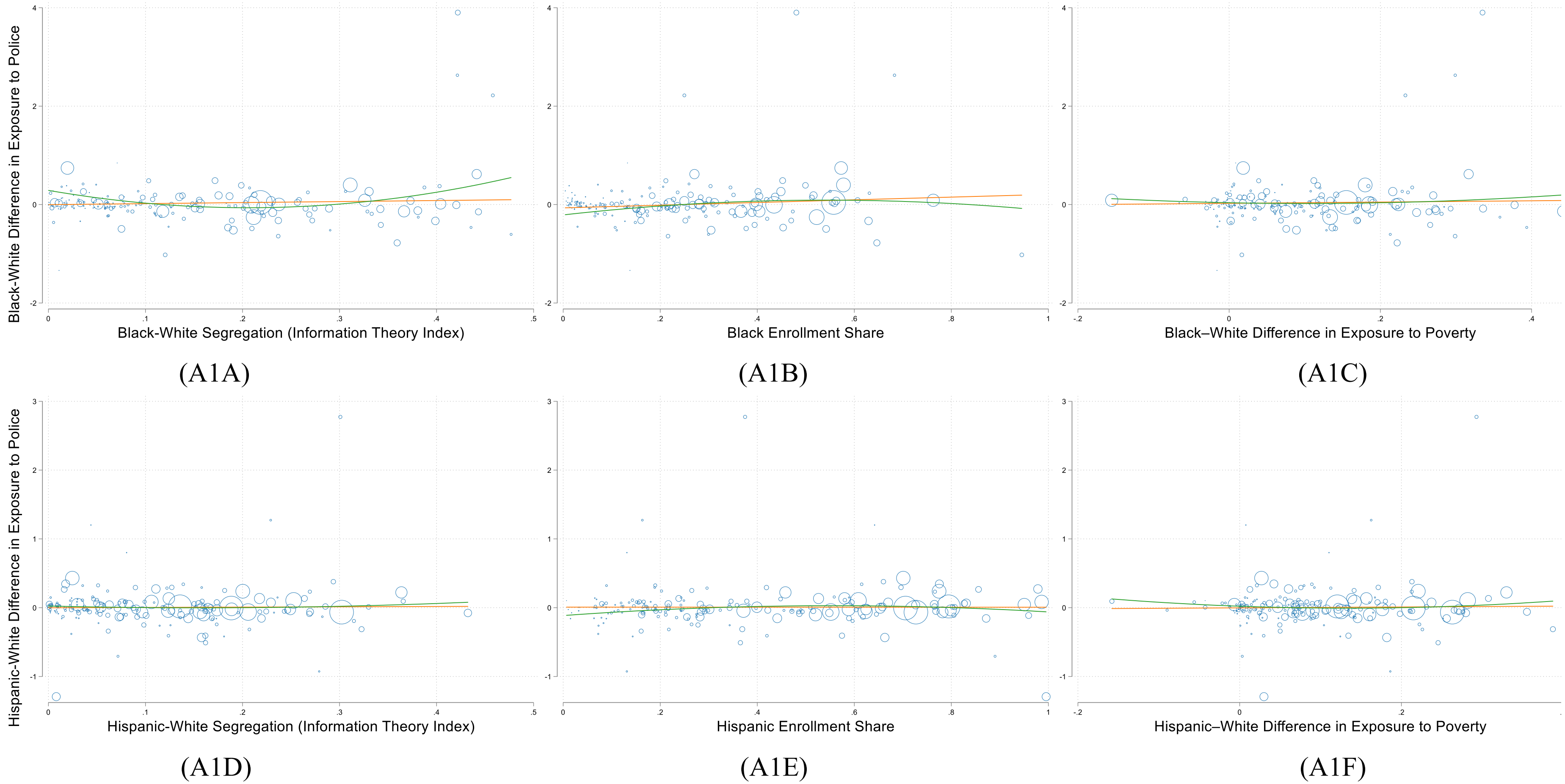
Black vs White Exposure					
2018 Gap Decomposition			2021 Gap Decomposition		
School Security Personnel	School Security Guards	Law Enforcement Officers	School Security Personnel	School Security Guards	Law Enforcement Officers
Overall Gap (USA)					
0.680	0.611	0.063	0.686	0.579	0.097
(0.000)	(0.000)	(0.000)	(0.866; 0.000)	(0.234; 0.000)	(0.031; 0.000)
Within Region Between Division					
0.006	0.025	-0.017	0.029	0.03	-0.001
(0.967)	(0.760)	(0.844)	(0.908; 0.847)	(0.961; 0.714)	(0.903; 0.991)
Within Division Between State					
0.072	0.056	0.016	0.087	0.068	0.019
(0.493)	(0.543)	(0.803)	(0.931; 0.554)	(0.928; 0.487)	(0.980; 0.859)
Within State Between District					
0.559	0.574	-0.019	0.468	0.526	-0.065
(0.000)	(0.000)	(0.486)	(0.372; 0.000)	(0.652; 0.000)	(0.572; 0.403)
Within District Between Schools					
0.165	0.120	0.042	0.211	0.102	0.104
(0.000)	(0.000)	(0.000)	(0.011; 0.000)	(0.195; 0.000)	(0.000; 0.000)
Between Region					
-0.122	-0.164	0.041	-0.109	-0.147	0.040
Hispanic vs White Exposure					
Overall Gap (USA)					
0.426	0.437	-0.033	0.376	0.455	-0.078
(0.000)	(0.000)	(0.000)	(0.066; 0.000)	(0.378; 0.000)	(0.000; 0.000)
Within Region Between Division					
0.017	0.020	-0.011	0.009	0.033	-0.025
(0.879)	(0.782)	(0.862)	(0.964; 0.944)	(0.902; 0.668)	(0.896; 0.754)
Within Division Between State					
0.129	0.144	-0.020	0.128	0.150	-0.023
(0.182)	(0.095)	(0.674)	(0.993; 0.345)	(0.966; 0.107)	(0.976; 0.809)

Within State Between District					
0.406	0.386	0.011	0.347	0.334	0.015
(0.000)	(0.000)	(0.757)	(0.562; 0.000)	(0.596; 0.000)	(0.967; 0.863)
Within District Between Schools					
0.032	0.020	0.009	0.055	0.023	0.031
(0.011)	(0.008)	(0.154)	(0.163; 0.000)	(0.743; 0.002)	(0.006; 0.000)
Between Region					
-0.158	-0.133	-0.022	-0.163	-0.085	-0.076

Notes: Gap estimates are based on regression estimates from Equation (1). P-values for the 2018 gap composition are based on the test of whether the gap is different from zero. For 2021, there are two p-values. The first p-value for the 2021 gap composition is based on the test of whether the 2021 gap is different from the 2018 gap, and the second p-value reflects the test of whether the 2021 gap is statistically different from zero. These estimates and, specifically, tests for differences in exposure gaps between 2018 and 2021 survey years are from regression equations from Online Appendix Equation 1. The between-region component of the gap is the residual of the overall gap minus the sum of the gaps at each geographic scale and is not estimated.

Appendix Figures

Figure A1. CBSA-Specific Gaps in Exposure to LEOs and Racial Segregation



Note: Figure plots the bivariate associations between Black-White and Hispanic-White differences in exposure to LEOs (Panels A1A-A1C and A1D-A1F, respectively) and three predictors of exposure (racial segregation, racial proportion, and racial difference in exposure to school poverty). Linear (orange) and quadratic (green) lines of best fit are weighted by the Black or Hispanic student share.