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District-Level Achievement Gaps Explain Black and Hispanic Overrepresentation in Special Education

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Abstract

To examine whether special education racial risk ratios reported by U.S. school districts are explained by district-level confounds, particularly, racial achievement gaps, we analyzed merged data (*N* = 1,952 districts for Black–White comparisons; *N* = 2,571 districts for Hispanic–White comparisons) from the U.S. Department of Education's Office of Civil Rights, Stanford Educational Data Archive, and Common Core data sets. Regression analysis results indicated that Black– and Hispanic–White district risk ratios were strongly related to Black– and Hispanic–White district achievement gaps. These results reconcile findings from district-level data with those from student-level data and support the finding that, when compared to otherwise similar White students by controlling for group differences in achievement, non-White students are on average underrepresented in special education. That is, non-White overrepresentation in special education in most districts is explained by racial achievement gaps in these districts. Residuals from the regressions provide a more accurate way to monitor for outlier districts than the current practice required in federal regulations of using unadjusted risk ratios.

Federal legislation and regulations require U.S. school districts to monitor for significant disproportionality in the extent to which students of color are overrepresented in special education (U.S. Department of Education [USDoE], 2016b). For example, the Equity in IDEA [Individuals With Disabilities Education Improvement Act] expands IDEA's mandated monitoring of significant disproportionality by requiring U.S. states to set "reasonable" prespecified risk ratio thresholds. School districts reporting significant disproportionality above prespecified risk ratio thresholds would be required to take corrective action. This is because school districts reporting significant disproportionality might be inappropriately overidentifying students of color as having disabilities based on their race or ethnicity (Albrecht et al., 2012; *Overidentification Issues Within the IDEA and the Need for Reform*, 2001; USDoE, 2016b).

U.S. school districts reporting significant disproportionality above prespecified risk ratio thresholds are required to (a) review and report annually on their disability identification policies, practices, and procedures; (b) identify and address school-based factors contributing to the observed significant disproportionality; and (c) reallocate up to 15% of their federal funding for special education.

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The Equity in IDEA regulations were intended to result in greater numbers of school districts being identified with significant disproportionality (USDoE, 2016a), which has been thought to be widely underreported (USDoE, 2016a; U.S. Government Accountability Office, 2013). However, the USDoE (2018) sought to delay implementation of these regulations to conduct further study, including whether districts should use unadjusted risk ratios to monitor for significant disproportionality. A federal district court recently ordered the regulations to be implemented (*Council of Parents, Attorneys, and Advocates v. USDoE*, 2019).

Limitations of Using Unadjusted Risk Ratios to Monitor for Significant Disproportionality

The Equity in IDEA regulations require U.S. school districts to calculate risk ratios as a standard reporting measure of significant disproportionality (USDoE, 2016b). Risk ratios here are the probability of receiving special education services of a specific racial or ethnic group (e.g., students who are Black or Hispanic) relative to the probability of receiving special education services of a comparison group (e.g., students who are White). For example, if 20% of students who are Black in a district were in special education, compared to 10% of students who are White, the Black–White risk ratio would be 0.2/0.1 = 2.0. Risk ratios greater than 1.0 directionally indicate overrepresentation of students of color in special education. Risk ratios less than 1.0 directionally indicate underrepresentation. The USDoE (2016b, p.4) proposed a threshold of two median absolute deviations (MADs) above or below the national median of local educational agencies (LEAs) to indicate that a district's risk ratio is an "outlier" and may indicate significant disproportionality in special education. Staff of the federally funded IDEA Data Center have suggested that state staff define outlier districts as those with risk ratios exceeding 1.5 times the interquartile range of risk ratios for all districts in the state (Crain & Lysy, 2017). These suggestions seem to reflect a known feature of a normal (Gaussian) distribution in which the area under the curve at two standard deviations above and below the mean accounts for 2.5% of the observations in each tail, so that one is identifying the 5% most extreme cases in the two tails combined. But the proportion under the tails may not be the same in non-normal distributions as it is in normal distributions, as is apparently the case for district risk ratios. Thus, applying the two-MAD standard nationally, USDoE (2016b, Table 1) data reveal that fully 8.2% of districts are above the cutoff for the representation of Blacks. Thus, if one includes districts more than two MADs below the cutoff, approximately 16.4% of all districts nationally would be considered as having Black risk ratios out of compliance with IDEA. This is far above the 5% most extreme cases usually used to define outliers. In addition, on a state-specific basis, this report finds some states with a much larger share of districts out of compliance. For example, the report finds that California and Texas have, respectively, 14.2% and 13.6% of districts above two MADs from the national median. If districts that are below two MADs are included, these two states would have approximately twice as many districts identified as outliers; that is, about a quarter of their school districts would be considered to have significant disproportionality. This is inconsistent with the idea that outliers should represent a relatively small number of very extreme cases.

These issues aside, not all districts are equivalent. Special education is to be provided to those students whose disabilities adversely affect their educational performance, a major indicator of which is academic achievement (National Research Council, 2002). Academic achievement is considered "the key variable in special education eligibility for most students" (Hosp & Reschly, 2004, p. 196). Some districts, perhaps because there is a particularly large gap between the education and income of White and Black families in the district, may have a more extreme imbalance between the needs of students from each group for academic assistance. Examples include Berkeley and Oakland, California, where children from affluent and well-educated White families employed at the University of California live in close proximity to, and often attend schools with, children from low-income Black and Hispanic families. Without adjustment for differences in White- and non-White needs for academic assistance, districts such as these may be inaccurately identified as using discriminatory practices. Yet evidence of racial discrimination is often taken to indicate that otherwise similar individuals of different races are treated differently.

More generally, students of color are more likely to experience greater exposure than students who are White to potentially harmful conditions during childhood, including poverty, low birth weight, and lead and other environmental toxins. Consequently, disability prevalence rates likely differ between students of color and students who are White (National Center for Education Statistics, 2017; National Research Council, 2002). Group differences in exposure to poverty and other risk factors result from historical and ongoing discrimination often resulting in residential segregation. Using unadjusted risk ratios to infer systemic bias may therefore result in spurious conclusions. Instead, adjusting risk ratios for racial achievement gaps would provide a better test of potential bias in disability identification practices. The National Research Council (2002) suggested that lesser disproportionality would be observed in districts with smaller achievement gaps.

How Can District Racial Risk Ratios Be Adjusted for Differential Service Needs?

Regression analysis is a standard tool for estimating the relation between a dependent and independent variable while adjusting for one or more other variables that may be correlated with both. However, in the case of risk for identification as having a disability, regression analyses are complicated by the issue of what unit of analysis should be used to measure the variables. Variables can be measured at the student level, or these student-level variables can be aggregated to produce variables measured at the district level, in which case they are referred to as ecological variables. The phenomena under investigation occur at the student level. Each student is or is not recommended for special education through a process typically beginning when a teacher observes the student performing below others in the class. This culminates in a committee meeting including the student's parents that decides whether the student has a disability that requires the provision of specialized services through an individualized education program (IEP). Accordingly, it is best to run a regression explaining disability identification using student-level data, including race or ethnicity, while also adjusting for possibly confounding variables by adding student achievement and other variables to the equation. Teacher-, school-, and district-level variables can also be added as additional controls. Such calculations were first reported using nationally representative student-level data by Hibel et al. (2010). They found that student achievement was by far the strongest predictor of disability identification. Controlling for achievement, students of color were on average less likely to be identified than students who are White. This finding has been observed using different data sets and statistical methods (Morgan et al., 2012, 2015, 2018; Morgan, Farkas, Hillemeier, et al., 2017, 2018) as well as by other researchers analyzing other databases (Cooc, 2019; Fish, 2019; Shifrer et al., 2011). In general, student-level data with controls for achievement indicate that, on average, students of color are underidentified as having disabilities relative to similarly situated students who are White.

Skiba et al. (2016) critiqued reports by Morgan and colleagues and, relying on district-level racial risk ratios collected by the Office of Civil Rights (OCR) of the USDoE, maintained that non-Whites are overrepresented in special education (for a reply, see Morgan & Farkas, 2016). Skiba and colleagues argued that the

OCR data are the most complete because they are a population survey rather than random samples. Importantly, these are the data that might be used by the USDoE and state governments to monitor individual districts for racial disproportionality. Morgan and colleagues as well as other researchers analyzing student-level data have found that group differences in achievement are an important confounder of the relation between race or ethnicity and disability identification. Unadjusted student-level data (i.e., without controls) show overrepresentation of non-White students. Once these data are adjusted for potential confounds, they show underrepresentation of non-White students. District-level data show overrepresentation with no controls but have not been analyzed using appropriate controls for group achievement differences. The question that then arises is whether it is possible to take district-level data and adjust them for the confound of group achievement differences. We do so in this study and show how the resulting methods could be used to monitor districts nationwide for significant disproportionality. We also show implications for the debate regarding the over- versus underrepresentation of non-White students in special education.

Modeling individual-level events using aggregate-level data may result in spurious inferences due to the ecological fallacy. In the ecological fallacy, relations between factors measured at the ecological or aggregate level (e.g., school districts) often fail to give the same results when these relations are estimated with individual-level data (Robinson, 1950). However, and in specific situations, it is possible for analyses of district-level data to approximate the results using individual-level data. For example, Hanushek et al. (1974) found that results from aggregate-level analysis closely resembled those from individual-level analysis if the aggregate-level regression included district-level measures of factors measured at the student level. Because group achievement differences are a strong confound of significant disproportionality attributed to systemic bias (National Research Council, 2002), district-level regressions controlling for group achievement differences might approximate findings from student-level regressions controlling for student-level achievement.

Prior regression studies of ecological data on significant disproportionality have not accounted for group achievement gaps. For example, Skiba et al. (2005) used district-level data from one midwestern state to examine whether poverty explained significant disproportionality in special education. The study's regression analyses predicted district Black–White special education disproportionality. Explanatory variables included the district-level average third-grade score on the state's accountability measure as well as average SAT scores. Yet for this district-level regression to control adequately for achievement differences, the Black–White achievement gap within each district should have been controlled. Instead, the investigators controlled each district's overall average achievement. Consequently, the inference by the investigators that racial bias was leading to Black overidentification for special education may have been spurious. Other studies using district-level data have also failed to account for district-level achievement gaps when reporting on disproportionality (e.g., Coutinho et al., 2002).

Study's Purpose

We sought to extend the knowledge base by including Black–White and Hispanic–White achievement gaps as well as other covariates measured at the district level in analyses of the racial risk ratios in the OCR data for several thousand districts nationwide. If these achievement gaps are significant explanatory factors, then the resulting regression equations demonstrate a methodology that could be used by federal and state policymakers to adjust their OCR data-based racial risk ratios for district differences in the relative needs of White and non-White students for special education services. Further, these estimated regressions are prediction equations that show the predicted racial risk ratio for districts as their racial achievement gaps become smaller and approach zero. If, when the achievement gap is zero, the predicted racial risk ratio is above 1.0, this would suggest that even after accounting for group differences in potential need for services, Black and Hispanic students are overrepresented in special education, conflicting with the findings reported by researchers analyzing student-level data. Alternatively, if an achievement gap of zero predicts a racial risk ratio of 1.0 or below, this would be consistent with the analyses of student-level data indicating that any observed overrepresentation of non-Whites in special education may be explained by group achievement differences (National Research Council, 2002). We therefore investigated the following research question, separately for students who are Black or Hispanic:

> Do analyses of district-level data replicate results from student-level data by indicating that students who are Black or Hispanic are not overrepresented in special education relative to students who are White after accounting for district-level achievement gaps? That is, do racial or ethnic achievement gaps explain the overrepresentation of Black and Hispanic students in special education observed in U.S. school districts?

Do racial or ethnic achievement gaps explain the overrepresentation of Black and Hispanic students in special education observed in U.S. school districts?

Consistent with findings from student-level analyses, we also hypothesized that the relation between district achievement gaps and risk ratios would continue to be evident despite statistical control for additional explanatory factors and that, after controlling achievement gaps, non-White students would be less likely to be identified as having disabilities when compared to otherwise similar students who are White.

Method

OCR Data Set

We used the public-use version of the 2013-14 USDoE's OCR data set (https://www2.ed.gov/about/offices/list/ocr/docs/crdc-2013-14.html). This data set included information collected via the biennial Civil Rights Data Collection (CRDC) survey on student enrollment, services, and outcomes, disaggregated by race-ethnicity, gender, limited English proficiency, and disability (USDoE, 2016a). The 2013–2014 CRDC collected data from the universe of all public school districts including schools serving students with disabilities. The initial target population included 17,106 districts. Some districts merged, closed, or otherwise changed. This resulted in a revised target population of 16,893 districts. Districts submitted data for the CRDC by typing it into an online tool or by uploading files in a comma-separated values format. The submission was certified by district-authorized personnel. Certified data were available for 16,758 districts in the 2013–2014 file used in these analyses (USDoE, 2016a). These districts, defined by the USDoE as LEAs, also included public organizations providing schooling to students but in ways that differed from traditional local districts serving a full range of students in multiple schools at different grade levels in that they included charter schools, alternative schools, juvenile justice facilities, and schools serving only students with disabilities.

Stanford Education Data Archive (SEDA)

We merged the OCR data set with the SEDA data set (Version 1.1; Reardon et al., 2017; https://cepa.stanford.edu/seda/download?nid=2016&destination=node/2021). We used the 2013 SEDA data set files that included school district–level means and standard deviations of mathematics and reading achievement scores. These data were collected for students in third through eighth grades and were reported separately by racial-ethnic subgroup (Fahle et al., 2017). The SEDA data set also provided information on Black– and Hispanic–White achievement gaps in school districts. Achievement data were constructed by SEDA using data available from the USDoE's EdFacts data system (https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html). The SEDA data set provided estimates of socioeconomic and demographic data for school districts obtained from the Common Core of Data (https:/nces.ed.gov/ccd/). To ensure confidentiality and data quality, the SEDA excluded school districts in which (a) racial or ethnic subgroup data were based on fewer than 20 students or (b) participation in the achievement testing was lower than 95% or the total number of achievement test scores reported by race, ethnicity, or gender was lower than 95% of the total number of scores for all students.

Analytic Variables

Black– and Hispanic–White risk ratios for special education service receipt. The risk ratio for special education service receipt for a specific racial or ethnic group was calculated using counts from the OCR database in the same manner as used by the federal government (e.g., USDoE, 2016b). The following disabilities were included in this variable: autism, emotional disturbance, intellectual disabilities, other health impairments, specific learning disabilities, and speech or language impairments. We computed risk ratios by dividing the percentage of Black or Hispanic students receiving special education by the percentage of White students receiving special education. For the resulting variable, we interpreted risk ratios above and below 1.0 as directionally consistent with over- and underrepresentation, respectively, for Black or Hispanic students compared to White students. As noted by Bollmer et al. (2007), this is not the only possible definition of the risk ratio. An alternative would be to use all students other than the minority group (e.g., non-Black or non-Hispanic students) as the comparison group rather than White students. However, the risk ratio would then be dependent on the racial composition of the district. To avoid this, we used White students as the comparison group. This was also consistent with the achievement gap measures used, in which the average achievement of Black or Hispanic students within each district was compared to that of White students.

Black– and Hispanic–White mathematics and reading achievement gaps. Reading (English language arts [ELA]) and mathematics achievement gap information was available from the SEDA data as described previously. We ran separate analyses, first using math achievement gaps and then using ELA achievement gaps as factors explaining the racial risk ratios. The results were very similar. We report those for math achievement gaps in the main body of the article. Those for ELA are reported in the online supplementary materials (Tables S6 to S8, Figures S1 and S2).

School district student enrollment. We viewed a district's size as measured by its student enrollment as a potentially important explanatory variable. This is because, as detailed subsequently and following USDoE practice, we restricted analyses to districts with at least 10 Black or Hispanic and White students in special education. This reduced the sample of districts by approximately 75%. That is, the great majority of districts in the database are quite small or are racially homogeneous. It is always a concern when the analysis sample is much smaller than the full database. However, districts deleted because they had too little racial diversity in special education would not contribute reliable information to the study.

Our analysis sample included about 2,000 districts nationwide. This number of districts should provide a large enough sample for reliable statistical results and that included racially diverse enrollments where significant disproportionality might be expected to be especially likely to occur. However, even within this sample, special education participation may vary according to district size. To control for this possibility, we included a dummy variable for whether a district had an enrollment of 10,000 to 50,000 and another dummy variable for whether a district had more than 50,000 students. These dummy variables contrasted middle- and larger-sized districts to smaller-sized districts. In addition, we interacted these dummy variables with the achievement gap variable to examine whether special education service receipt varied by district size. This also evaluated for the possibility that the deleted districts, which tended to have low enrollments, displayed identification dynamics that differed from those of larger districts. Enrollment counts in total and by racial or ethnic group were used from the OCR database.

Free or reduced-price lunch. The percentage of students qualifying for free or reduced-price lunch and the percentages of Black and Hispanic students were taken from the 2013 Common Core of Data and scaled as decimals (e.g., 20% = .20). We used the percentage of students qualifying for free and reduced-price lunch as a measure of district-level poverty. We included this variable as a control following prior studies that included a predictor for the average of either the socioeconomic status (SES) or the poverty status of students. However, the direction of the relation with district-level SES is currently unclear. On the one hand, being in a higher-poverty district should expose more students to the risk factors for disabilities, thereby increasing a district's percentage of students needing special education services (Skiba et al., 2005). On the other hand, being in a higher-poverty district should lower the likelihood of special education service receipt because of a "frog pond" effect, whereby a larger percentage of low-income and therefore low-achieving students reduces the disability identification rate for students with similar achievement. This is because being in a higher-poverty district lowers the threshold in which a student's achievement is viewed as substantially below their classmates and so as potentially indicative of a disability (Hibel et al., 2010). Another reason for a reduced identification rate in low-achieving districts is that if a higher achievement standard (such as may be used in lower-poverty districts) is used, so many students will qualify for special education as to exceed the capacity of the district's special education program (and budget) to serve them.

We also included state fixed effects in the regressions. These equations were estimated by using "proc glm" in SAS (we used SAS 9.4 for all analyses), with state id in the Absorb statement. This was equivalent to adding a dummy variable for each state and suppressing the intercept and the dummy variable coefficient estimates. These fixed effects account for the possibility that states differ significantly in racial risk ratios even after controlling other explanatory factors.

Data Cleaning

The USDoE (2016b, p. 8) report analyzing the OCR data stated,

> These LEA-level data . . . did not undergo data quality procedures and therefore are not subjected to the same level of scrutiny (i.e., edit checks, analysis of and accounting for year to year changes, etc.) as the state-level data. As such, the overall quality and accuracy of these data is unknown.

We therefore began by examining the OCR-SEDA data set in order to restrict attention to reliable data points with non-missing scores on the study's variables. Figure 1 displays the steps taken to prepare the data sets for analysis, separately for the Black– and Hispanic–White data sets.

The 2013–2014 OCR data described 16,758 school districts. However, many of these districts had low enrollment or few Black or Hispanic students and therefore very few Black or Hispanic students in special education. Thus, we used the USDoE (2016b) methods by creating an analytical sample that included only school districts where at least 10 Black and 10 White or 10 Hispanic and 10 White students received special education. This reduced the Black and Hispanic analytic samples to 4,142 districts and 5,064 districts, respectively.

We next removed any cases with data reporting inconsistencies (e.g., more Black students receiving special education than

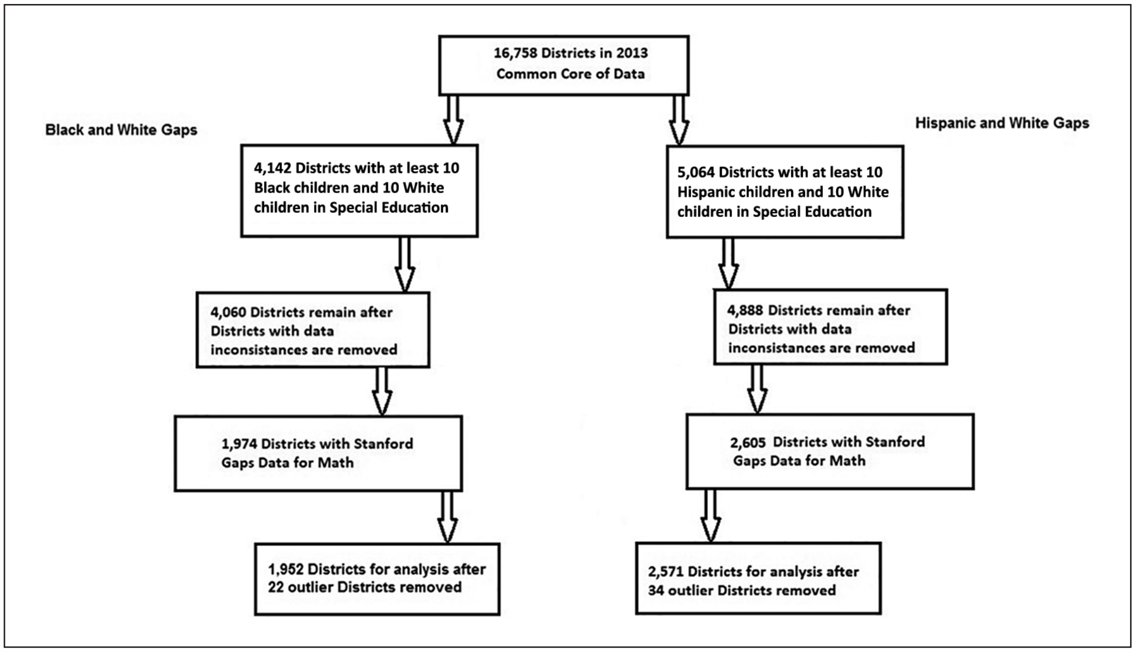

Figure 1. Office of Civil Rights school district data with necessary deletions and after matching with Stanford data on math achievement gaps.

were reported as enrolled in the school district). This left 4,060 and 4,888 districts for the Black– and Hispanic–White analyses, respectively. We next restricted analysis to those districts that, after merging the OCR and SEDA data, had nonmissing data for the Black– and Hispanic–White achievement gaps. This left 1,974 and 2,605 districts for the Black– and Hispanic–White analyses, respectively. We then estimated regression models in which we used covariate adjustment including for Black– and Hispanic–White achievement gaps when estimating the Black– and Hispanic–White risk ratios.

Data Analysis

We first examined descriptive statistics for each of the data sets. We constructed histograms of the distribution of the risk ratio for racial subgroups. This allowed us to see the prevalence of unadjusted risk ratios above 1.0 (i.e., directionally indicative of overrepresentation) and below 1.0 (i.e., directionally indicative of underrepresentation). We then ran a series of regression models to explain district-level variability in the Black– and Hispanic–White risk ratios. Model 1 used only the district's racial achievement gap as a covariate. Model 2 added this variable squared to the equation to account for possible nonlinearity in the relations between these variables. Models 3 through 5 added additional covariates. Models 4 and 5 included state fixed effects. These regression models allowed us to examine whether ecological regressions using district-level data indicated a strong relation between a district's Black and Hispanic risk ratios and achievement gaps and, if adjusted for such achievement gaps, yielded evidence consistent with studies analyzing student-level data. If so, this would suggest how analyses of district-level data might be used by state and federal policymakers to monitor for significant disproportionality. The resulting risk ratios would then be tested for statistical significance before they were considered evidence of significant disproportionality. We used a district's standardized residual of greater than two standard deviations from the regression line as an indicator of possible significant disproportionality that was unlikely due to either the confound of achievement gaps or chance fluctuation.

Table 1. Descriptive Statistics for Each of the District-Level Data Sets.

Variable	Black–White analysis (N = 1,952 districts)		Hispanic–White analysis (N = 2,571 districts)	
	M	*SD*	*M*	*SD*
Minority disproportionate risk ratio	1.21	0.35	0.98	0.34
Minority math gap (standard deviation units by SEDA)	0.66	0.24	0.45	0.24
School district has <10,000 students	0.69	0.46	0.75	0.43
School district has 10,000 to 50,000 students	0.27	0.44	0.22	0.42
School district has >50,000 students	0.04	0.20	0.03	0.17
Percentage of free or reduced-price lunch in district	0.48	0.21	0.42	0.20
Minority Math SEDA Gap × School District has 10,000 to 50,000 students	0.18	0.32	0.10	0.22
Minority Math SEDA Gap × School District has >50,000 students	0.03	0.16	0.02	0.10
% Minorities in district	0.22	0.19	0.28	0.22

Note. SEDA = Stanford Education Data Archive.

When estimating Model 1, we followed the standard practice of removing outliers that were more than three standard deviations from the fitted regression line. This removed 22 out of 1,974 districts for the Black–White analysis and 34 out of 2,605 districts for the Hispanic–White analysis. Removing these outliers allowed us to estimate the regression line representing the overall population relations without the estimates being unduly affected by possible miscoding and other data set idiosyncrasies despite our data-cleaning checks. We saw no pattern in these outliers (the list of specific districts and their enrollments and standardized residuals are available from the first author).

Results

Descriptive Analyses

Table 1 displays descriptive statistics for the district-level variables, separately for the Black– and Hispanic–White analytic samples. The mean and standard deviation of the Black–White risk ratio were 1.21 and 0.35, respectively. The mean and standard deviation of the Hispanic risk ratio were 0.98 and 0.34, respectively. This average unadjusted Black–White risk ratio was consistent with prior reporting of overrepresentation (e.g., Morgan, Farkas, Cook, et al., 2017; Skiba et al. 2005), although prior to adjustment for district-to-district variation in the Black–White achievement gap. The unadjusted Hispanic average risk ratio of 0.98, with a standard deviation of 0.34, indicated no Hispanic overrepresentation for the average district. Table 1 also shows that the Black– and Hispanic–White achievement gaps averaged 0.66 and 0.45, respectively. (Achievement gaps were on an additive scale, so 0.0 indicated the absence of a gap.)

Regression Analyses

Tables 2 and 3 display results from analyses in which the district-level Black– and Hispanic–White risk ratios were regressed against the district-level Black–White and Hispanic–White achievement gaps and additional covariates. Table 2's Model 1 regresses the district-level Black–White risk ratios against district-level Black–White achievement gaps. The result was an intercept of 0.75 and a highly significant regression slope of 0.70. The R^2 was .23. Thus, the predicted Black–White risk ratio for districts with a Black–White achievement gap of zero was 0.75. This estimate was directionally consistent with

Table 2. Regression Analysis of Black–White Special Education Risk Ratio, 2013 OCR/SEDA Merged Data.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.75***	0.83***	0.83***	—	—
Black–White math achievement gap in standard deviation units	0.70***	0.46***	0.49***	0.47***	0.40***
Black–White math gap squared		0.17**	0.16**	0.18**	0.19**
Enrollment 10,000 to 50,000 students			−0.04*	−0.10*	−0.13**
Enrollment > 50,001 students			−0.11**	0.03	0.04
Minority Math Gap × 10,000 to 50,000 Students				0.13	0.16*
Minority Math Gap × >50,001 Students				−0.16	−0.15
Percentage of free or reduced-price lunch students in school					−0.18***
% Black children in district					−0.13**
State fixed effects				X	X
F value	596.11	303.10	155.67	20.19	20.96
R^2	0.23	0.24	0.24	0.33	0.35
Standard deviation of the residuals	0.30	0.30	0.30	0.29	0.28

Note. OCR = Office of Civil Rights; SEDA = Stanford Education Data Archive. *N* = 1,952 districts.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 3. Regression Analysis of Hispanic–White Special Education Risk Ratio, 2013 OCR/SEDA Merged Data.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.71***	0.73***	0.74***	—	—
Hispanic–White math achievement gap in standard deviation units	0.61***	0.49***	0.52***	0.35*	0.21**
Hispanic–White math gap squared		0.12	0.10	0.21***	0.25***
Enrollment 10,000 to 50,000 students in district			−0.08***	−0.05	−0.06*
Enrollment > 50,001 students in district			−0.06	−0.08	−0.04
Minority Math Gap × 10,000 to 50,000 Students in District				0.05	0.07
Minority Math Gap × >50,001 Students in District				0.08	0.06
Percentage of free or reduced-price lunch students in school district					−0.52***
% of Hispanics in school district					0.23***
State fixed effects				X	X
F value	546.40	275.07	146.70	29.58	35.54
R^2	0.18	0.18	0.19	0.35	0.40
Standard deviation of the residuals	0.31	0.31	0.31	0.28	0.27

Note. OCR = Office of Civil Rights; SEDA = Stanford Education Data Archive. *N* = 2,571 districts.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

underrepresentation, a result also reached by prior research analyzing student-level data and adjusting for student-level achievement (e.g., Hibel et al., 2010; Morgan et al., 2012, 2015; Morgan, Farkas, Hillemeier, et al., 2017). The regression equation indicated that a one-standard-deviation increase in a district's Black–White achievement gap was associated with a 0.70 increase in a district's Black–White risk ratio.

Table 2 presents results for Model 2, which included a squared term for the achievement gap. This term was statistically significant and indicated that the slope of the risk ratio against the achievement gap was steeper at higher values of the achievement gap. However, adding this term increased R^2 by only .01. The slightly increased value of the intercept in Model 2 indicates that a district with no Black–White achievement gap would be expected to have a risk ratio of 0.83, still in the direction of underrepresentation. Adjusting for district-level achievement gaps indicated that Black students were less likely to be in special education than similarly achieving White students.

Adjusting for district-level achievement gaps indicated that Black students were less likely to be in special education than similarly achieving White students.

In Models 3, 4, and 5 of Table 2, we added additional covariates to the regression equation. Models 4 and 5 added state fixed effects. Districts with enrollments in the 10,000-to-50,000 student range tended to have lower Black–White risk ratios than smaller districts, whereas coefficients for the largest districts (>50,000 students) lost significance in Models 4 and 5. The interaction terms showed that the relation between the achievement gaps and risk ratios were also stronger in medium-sized than in very small or very large districts. Adding state fixed effects to the equation increased R^2 substantially from .24 to .33, suggesting that states differed meaningfully in their Black–White risk ratios. Consistent with the frog pond hypothesis (Hibel et al. 2010), a district's percentage of free and reduced-price lunch students was associated with a lower risk ratio. With these covariates in the equation, the district's percentage of Black students had a significant negative effect on the risk ratio. Overall, these results indicated that, following control for additional district-level variables, the achievement gap continued to be significantly and positively related to the Black–White risk ratio for special education service receipt.

Table 3 shows these analyses repeated with the Hispanic–White sample. Results from Table 3's Model 1 were consistent with Table 2's Model 1 results. Model 1 indicated that a district with no Hispanic–White achievement gap would be expected to have a Hispanic–White risk ratio of 0.71, similar to the analogous Black–White risk ratio of 0.75. The achievement gap slope of 0.61 for Hispanic students was also similar to the slope estimated for Black students, again indicating that district-level risk ratios were positively and strongly related to district-level achievement gaps. This result was again consistent with the underrepresentation of Hispanic students in special education found when analyzing student-level data (Morgan, Farkas, Hillemeier, et al., 2017). The results of Model 2, which added the square of the achievement gap to the equation, appear in Table 3. As with the analysis for Black students, this was positive but was not statistically significant for Hispanic students. The intercept increased by only 0.02, to 0.73 in Model 2, again indicating underrepresentation of Hispanic students in districts with no Hispanic–White achievement gap.

Analyses of Model 3 showed that, as for Black students, medium-sized districts had somewhat smaller Hispanic–White risk ratios than the smallest districts. The interactions in Model 4 were not significant, indicating that the relation between Hispanic–White risk ratios and achievement gaps did not vary significantly across district size. The addition of state fixed effects in Model 4 increased R^2 substantially, from .19 to .35, indicating that, as for Black students, states differed substantially in their Hispanic–White risk ratios. Model 5 showed that a district's poverty rate was strongly and negatively associated with a decreased Hispanic–White risk ratio (coefficient = -0.52, $p < .001$), again supporting the frog pond hypothesis. However, the percentage of Hispanic students in the district was positively associated with the Hispanic–White risk ratio (coefficient = 0.23, $p < .001$). Because (a) districts with high percentages of Hispanic students also tended to have high poverty rates and (b) the coefficient for percentage poor was larger than that for percentage Hispanic, any increase in the percentage Hispanic students, which would also covary with an increase in the percentage poor, would lower the Hispanic–White risk ratio. Overall, the inclusion of additional covariates indicated that the relation between the Hispanic–White risk ratios and achievement gaps was robust. Across both Tables 2 and 3, R^2 indicated moderate model fit.

We repeated these calculations using the district ELA achievement gap rather than the math achievement gap as an explanatory factor. The results are shown in Supplementary Tables S6, S7, and S8. Table S7 shows results very similar to Table 2 for the Black–White comparison, with a y-intercept of 0.81 instead of 0.71 and a slope of 0.65 instead of 0.70. Similarly, for the comparison of Tables 3 and S8 for Hispanics, the y-intercept in Table S8 is 0.75 instead of 0.71 and the slope is 0.45 instead of 0.61. Thus, all four analyses, whether for Blacks or Hispanics and whether using the math or the ELA achievement gaps as an explanatory factor, indicate that for districts with no racial achievement gap, a racial risk ratio below 1.0 is expected.

Scatterplots. Figure 2 shows the scatterplots of the district data points for the Black– and Hispanic–White risk ratio regressions (from Model 1 of Tables 2 and 3) as well as the estimated regression lines. These indicated a positive relation between the risk ratios and achievement gaps. A greater share of the districts in the Hispanic versus the Black analytical sample had achievement gaps close to zero, and appropriately, more of the districts in the Hispanic–White analysis had risk ratios below 1.0. The great majority of the included observations fell within the confidence intervals around the regression lines. Supplementary Figures S3 and S4 replicated these figures for the regressions using ELA as explanatory factors. We again observed that an achievement gap of zero was associated with a district racial risk ratio well below 1.0.

Regression residuals as goodness-of-fit diagnostics and indicators of disproportionality. We next examined the distribution of the standardized residuals (that is, the residual for each district divided by the standard deviation of the residuals) from the regressions in Model 1 of Tables 2 and 3. The residuals were approximately normally distributed, and the fitted regression lines represented the district-level plotted points well. Each district's regression residual represented its risk ratio adjusted for its achievement gap. The strong and significant relations found between district racial risk ratios and racial achievement gaps, the good fit of the data to the model, and the appropriate pattern of the residuals suggest that this type of analysis could be used by state and federal personnel to identify school districts whose racial risk ratios are outliers after adjusting for their racial achievement gaps. The results support using an absolute value of the standardized residual that is above 2.0 to identify districts where significant disproportionality may be occurring.

Nonparametric Analysis of the Relations Between the Black– and Hispanic–White Risk Ratios and Achievement Gaps

Because these regression lines were estimated from districts of which a majority had achievement gaps above zero, the regression model extrapolations to the situation of no achievement gaps may be inaccurate close to the value of zero. To investigate the risk ratios of districts with achievement gaps close to zero, we divided the achievement gap variable into groups of 0.2-standard-deviation widths. We then computed the mean and standard deviation of the risk ratio for each of the resulting group of districts. Doing so provided a nonparametric analysis of the relation between risk ratios and achievement gaps. Figure 3 displays these results, which provide an additional check of whether overrepresentation in special education was explained by racial achievement gaps. If so, then districts with small Black– or Hispanic–White achievement gaps would not be expected to display Black– or Hispanic–White risk ratios above 1.0. Instead, districts

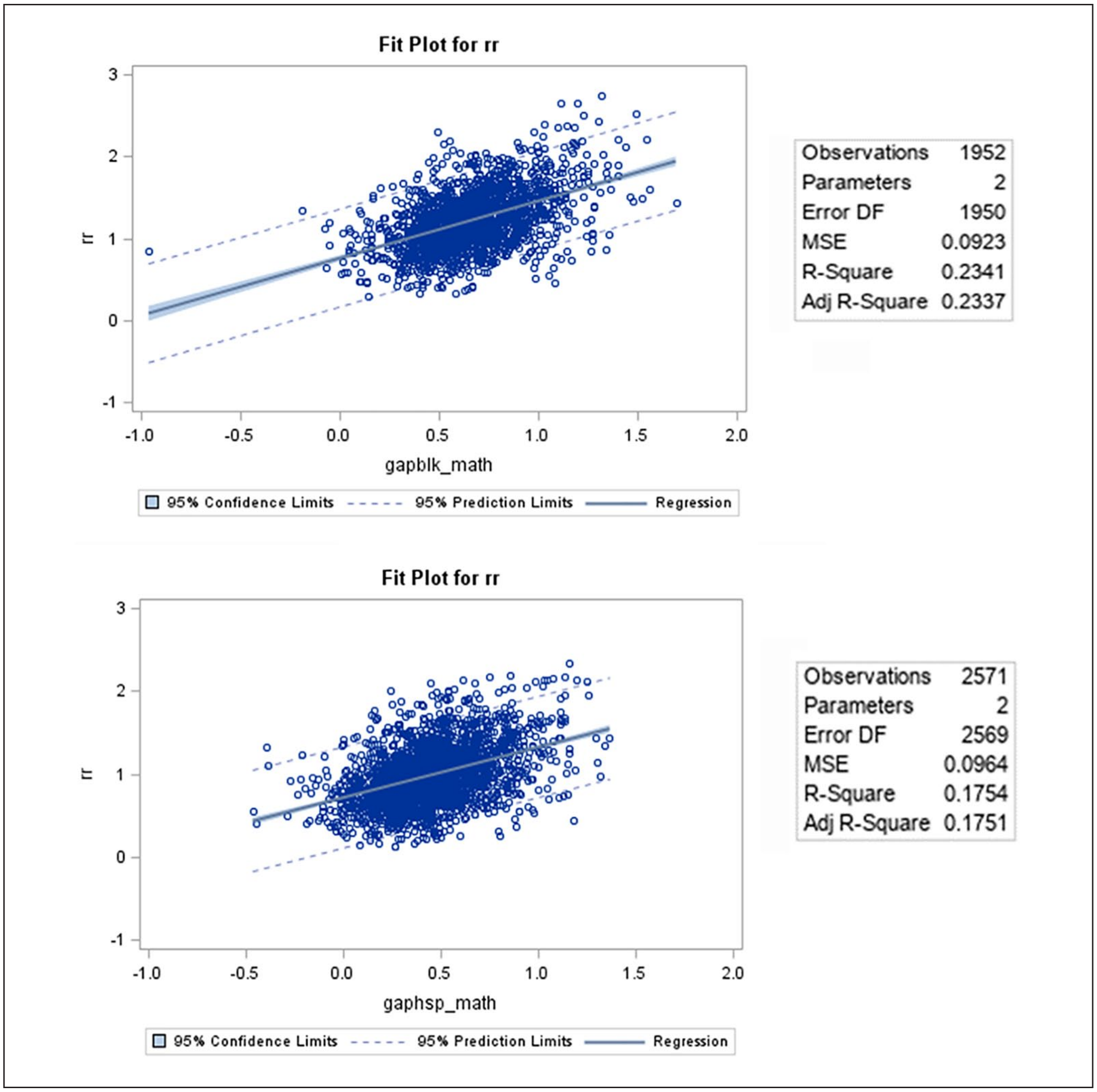

Figure 2. Top: Black–White risk ratio against Black–White achievement gap; Bottom: Hispanic–White risk ratio against Hispanic–White achievement gap.

with small achievement gaps should be reporting Black– or Hispanic–White risk ratios below 1.0. (Supplementary Table S5 shows the counts underlying Figure 3.)

For the Black–White analytic sample, only six districts had an achievement gap below zero. The risk ratios for these districts averaged 1.01 and so indicated neither under- nor overrepresentation. There were 41 districts with Black–White achievement gaps between 0 and 0.2 standard deviations. The risk ratios for these districts averaged 0.89 and so indicated underrepresentation. For the 170 districts with achievement gaps between 0.2 and 0.4 standard deviations, the average risk ratio was 0.99. Subsequently, and as the Black–White achievement gap increased, the average Black–White risk ratio increased monotonically to 1.09, 1.23, 1.40, 1.53, 1.63, and 1.83. This monotonicity is additional empirical evidence that district-level Black–White risk ratios were strongly related to district-level Black–White achievement gaps. As with analyses of individual-level data, analyses of district-level data showed that adjusting for achievement gaps, Black students tend to be underrepresented in special education. It was only when districts had a Black–White achievement gap above

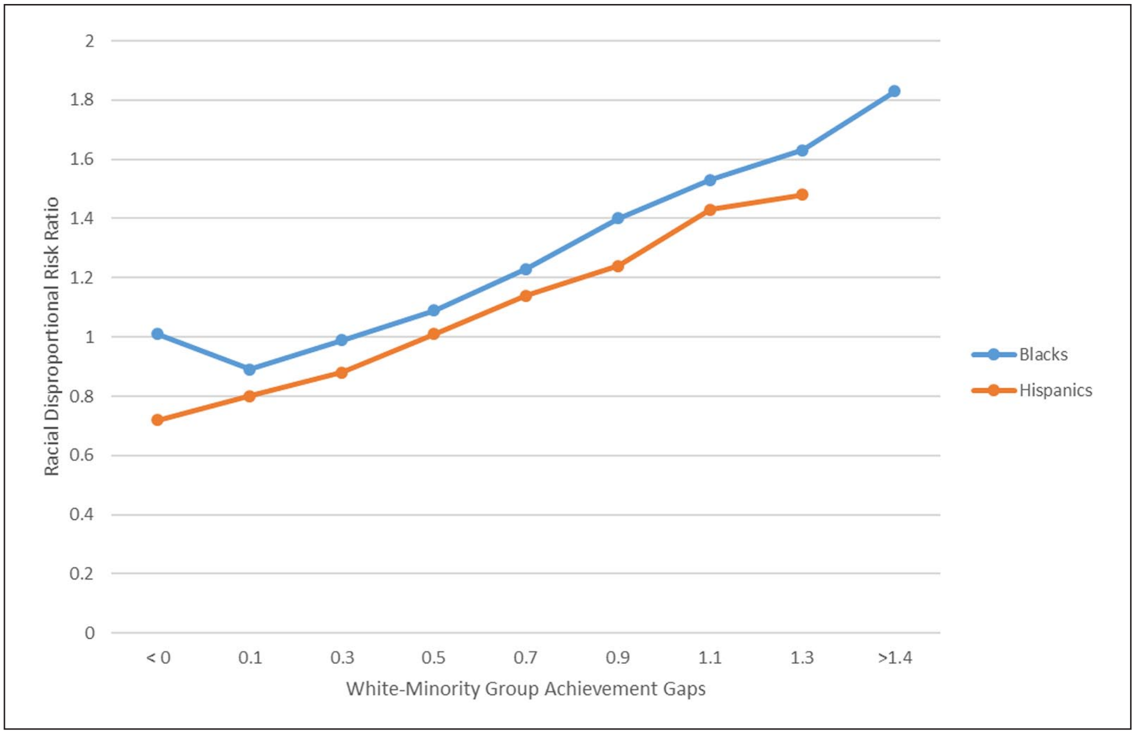

Figure 3. Mean value of risk ratio by groupings of achievement gap, separately for each analysis sample.

approximately 0.4 standard deviation that the Black–White risk ratio began to average above 1.0. As the Black–White achievement gap increased, the Black–White risk ratio increased monotonically. This is strong evidence in support of our research hypothesis. Specifically, district-level data analyses adjusted for district-level achievement gaps yielded risk ratio estimates directionally consistent with findings from student-level data analyses adjusted for student-level achievement.

The relation between the Hispanic–White risk ratios and achievement gaps was similar. As the Hispanic–White achievement gap increased, so did the average Hispanic–White risk ratio. The risk ratio averaged 0.72 for the 56 districts with a Hispanic–White achievement gap below zero. The risk ratio averaged 0.80 for the 270 districts with a gap between 0 and 0.2. As the achievement gap increased, the average Hispanic–White risk ratios increased monotonically: 0.88, 1.01, 1.14, 1.24, 1.43, and 1.48. As in the Black–White analyses, districts with Hispanic–White achievement gaps above 0.4 standard deviations tended to average Hispanic–White risk ratios above 1.0.

Figure 3 shows that for both racial-ethnic groups, there was a strong monotonic relation between a district's achievement gap and risk ratio. On average, the larger the district's Black– or Hispanic–White achievement gap, the larger the district's Black– or Hispanic–White risk ratio. This is the strongest evidence for the relation between risk ratios and achievement gaps because it imposes no functional form on this relation. Instead, we observed similar positive and linear relations for the Black–White and Hispanic–White risk ratios emerging by simply plotting their means against the respective achievement gaps. Figure 3 suggests that in the absence of these racial achievement gaps, there would be no overrepresentation of either Black or Hispanic students in special education on average.

On average, the larger the district's Black– or Hispanic–White achievement gap, the larger the district's Black– or Hispanic–White risk ratio.

Follow-Up Analyses of the Largest Districts and Regression Residuals

We next examined whether large school districts, typically with substantial percentages of Black or Hispanic students, displayed similar relations as detailed earlier. (Supplementary Tables S1 and S2 show the risk ratios and standardized regression residuals for the 20 largest districts in the Black–White and Hispanic–White regression analyses of risk ratios against achievement gaps.) Most of the Black–White odds ratios for these districts are above 1.0. However, they are not greatly above this value, with a median value of 1.29. These districts also had relatively small standardized residuals, approximately evenly divided between those above (45%) and below (55%) zero, indicating that their observed risk ratios were close to those predicted by their achievement gaps. The regression of risk ratios against achievement gaps provided a very good fit to these data. We repeated this calculation for the 20 largest districts, this time focusing on Hispanic–White risk ratios and achievement gaps. Nine of the 20 risk ratios are below 1.0 (i.e., in the direction of Hispanic underrepresentation), indicating that even without regression adjustment, almost half of the largest districts have a higher percentage of White than Hispanic students in special education. Further, as for the Black–White risk ratio, the standardized residuals are quite modest in size. We conclude that for the 20 largest U.S. school districts, Black and Hispanic risk ratios are explained by their achievement gaps.

Finally, we examined the largest positive and negative residuals from the fitted equations. Because we deleted districts with standardized residuals of more than three standard deviations from the fitted line as they are likely to involve errors or anomalies, the largest standardized residuals remaining are those whose absolute value is just below 3.0. The goal in examining these was to look for patterns in the size or geographic location of these districts that might suggest problems with our analysis. (These results are in Supplementary Tables S3 and S4.)

We examined the districts with the 10 most positive and the 10 most negative standardized residuals from the Black and Hispanic analyses (Supplementary Tables S3 and S4). We found that these 40 districts generally had small enrollments. For example, 83% of these districts had enrollments of fewer than 10,000 students. This is consistent with the fact that small districts, because of their smaller samples, would be likely to have more widely varying racial risk ratios due to larger sampling error. As for geographic location, there was no concentration of these districts in a particular region of the country. Although these districts may be candidates for further investigation of their disability identification practices, they also may be outliers simply because their relatively small enrollments result in more statistical fluctuations due to greater sampling error.

Discussion

For many years, analysis of OCR district-level racial risk ratios unadjusted for possible confounds have led to the belief that U.S. school districts are inappropriately overidentifying non-White students as having disabilities. To address significant disproportionality based on race or ethnicity in disability identification, federal legislation and regulations currently require U.S. states to monitor for such significant disproportionality using risk ratios. The USDoE (2016b) and the IDEA Data Center (Crain & Lysy, 2017) have detailed how this can be accomplished by state and federal auditors searching for districts with outlier values of their unadjusted racial risk ratios. Yet studies of nationally representative student-level data have found that controls for differences in academic need measured by test scores explain such overrepresentation and in fact suggest that—among similarly situated students—White students are more likely than non-White students to receive special education services in the United States (Hibel et al. 2010; Morgan et al., 2012, 2015; Morgan, Farkas, Hillemeier, et al., 2017). Yet missing has been an analysis of district-level data controlling between-group achievement differences. If such an analysis showed underrepresentation, then the student- and district-level findings would be consistent with one another.

Our study provides this analysis. Specifically, we hypothesized that there would be a strong relation between the size of the district's Black– and Hispanic–White achievement gaps and the district's Black– and Hispanic–White risk ratio, such that districts with smaller achievement gaps would report smaller risk ratios. We further hypothesized that the relation between district-level risk ratios and achievement gaps would continue to be evident after accounting for other explanatory factors. Evidence of this continued relation would be consistent with hypotheses and reports that group differences in special education service receipt are strongly related to group differences in academic achievement and that achievement is a particularly strong confound of inferences that significant disproportionality results from systemic bias (Morgan, Farkas, Cook, et al., 2017; Morgan, Farkas, Hillemeier, et al., 2017; National Research Council, 2002).

The estimated regressions showed that district-level risk ratios are strongly and monotonically related to district-level achievement gaps. On average, and across both samples, districts reporting risk ratios directionally consistent with overrepresentation also had sizeable achievement gaps. For example, we found on average that districts reported only Black–White risk ratios more than 1.0 that had Black–White achievement gaps above 0.4 of a standard deviation. The larger a district's achievement gap, the larger the district's risk ratio. Districts with Black–White achievement gaps below 0.4 of a standard deviation reported Black–White risk ratios that averaged or were below 1.0. These findings for the Black–White sample were replicated in the Hispanic–White sample. That racial disproportionality in special education was strongly related to a district's achievement gaps is consistent with hypotheses by the National Research Council (2002, p. 77). We found that regression analyses that adjusted for district-level racial risk ratios for racial achievement gaps yielded predicted values indicating that for most districts, their racial risk ratios are above 1.0 only when their racial achievement gaps are above zero. Analyzing risk ratios from the same OCR data that in the past have been used as evidence of non-White overrepresentation in special education, we found that risk ratios adjusted for achievement gaps yielded evidence of underrepresentation, consistent with recent but contested results from student-level data.

Results from the study's regression analyses also suggested a policy-relevant method to identify more accurately U.S. school districts that may be inappropriately over- or underidentifying students who are Black or Hispanic as having disabilities. This is because after regressing Black– and Hispanic–White risk ratios against the Black– and Hispanic–White achievement gaps, each sample's district had a regression residual (i.e., the difference between the district's predicted and observed risk ratio). These residuals were approximately normally distributed and showed how far the district's risk ratio is from what was predicted based on the district's achievement gap. That is, these residuals showed whether the district's risk ratio was higher or lower than expected based on the district's achievement gap and by how much. Most importantly, unusually large values of these residuals identified outliers whose values suggest that federal civil rights investigations of the district's disability identification procedures may be warranted. Our study demonstrates a method that can be used to identify districts where significant disproportionality is occurring that is not explained by achievement gaps.

Our study demonstrates a method that can be used to identify districts where significant disproportionality is occurring that is not explained by achievement gaps.

We examined the residuals from specific groups of districts, finding that none of the 20 largest districts were an outlier for either the predicted Black– or Hispanic–White risk ratios (Supplementary Tables S1 and S2). No evident pattern emerged from the list of positive and negative outliers. These outliers may have resulted from data errors or chance fluctuations. One possible improvement might be to repeat these analyses over multiple years and so give greater monitoring attention to districts whose regression residuals were outliers across multiple years. These districts might then be possible candidates for increased civil rights monitoring. Doing so would be consistent with the Equity in IDEA regulation's emphasis on identifying disproportionality that is "systemic or otherwise indicative of persistent problems" (Federal Register, 2016, pp. 92411, 92418; U.S. Department of Education, 2016c).

Limitations

We note several limitations of our study. Our results are not causal. We analyzed secondary data and report associations between district-level risk ratios, achievement gaps, and other factors. Students may display low achievement for many reasons. Use of the OCR data also limited the study. Beginning with 16,758 districts, restricting the data to districts with at least 10 Black and 10 White or 10 Black and 10 Hispanic students in special education, as well as no data anomalies (such as more students of a particular group in special education than in the district as a whole), necessitated deletion of approximately 75% of the districts for the Black–White analysis and about 67% of the districts for the Hispanic–White analysis. Further reduction of the sample to those districts for which racial gap achievement measures were available from SEDA, as well as checking for data inconsistencies and outliers, resulted in 1,952 and 2,571 districts for the Black– and Hispanic–White analyses, respectively. These data reductions may limit the generalizability of the study's findings. However, most of the deleted districts had small and possibly specialized student enrollments that limited their usefulness in monitoring for significant disproportionality. Further, we included district enrollment size dummy variables in the regressions and interacted these with the achievement gap to control any dependence of the estimated relations on district size. Thus, we believe that the findings generalize to all but the smallest U.S. districts, many of which have too few Black or Hispanic students to allow for reliable estimates of significant disproportionality.

Implications for Policy and Research

We found that district-level Black–White and Hispanic–White achievement gaps were strongly related to district-level racial risk ratios for disability identification. We also found that these achievement gaps explained racial risk ratios above 1.0 in many districts. These district-level results are consistent with student-level analyses suggesting that overrepresentation of non-White students in special education is largely explained by their greater likelihood of experiencing academic difficulties. This provides further evidence in the debate regarding whether non-White students are overrepresented in special education due to systemic bias. This evidence comes from analyzing the same OCR data that have been used to infer that overrepresentation has been resulting from systemic bias.

On a more practical level, we illustrated a method that could be used by state and federal auditors to evaluate districts for significant disproportionality. This methodology would not be difficult to implement. Under federal legislation, each state is required to test every student in Grades 3 through 8 and in one high school grade in math and ELA each year, and these data are available in EdFacts maintained by the USDoE. In addition, districts are required to report to the OCR the numbers of students of different racial and ethnic groups in the district as a whole and in special education for specific disabilities. With this information, a state agency could conduct regression analyses of racial risk ratios against racial achievement gaps for the state's school districts. The IDEA Data Center already provides an online manual for state employees to learn how to compute district risk ratio outliers, defined as falling outside 1.5 times the interquartile range of risk ratios (Crain & Lysy, 2017). The USDoE has already sought to implement district monitoring by training state personnel to identify districts with outlier racial risk ratios. Our suggestion is that the outliers be from a regression that adjusts for a district's racial achievement gaps and that attention be given to negative as well as positive outliers. Doing so would provide a more methodologically and substantively justifiable method for identifying U.S. school districts where significant disproportionality based on race or ethnicity may be occurring.

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