

Unproven Links: *Can Poverty Explain Ethnic Disproportionality in Special Education?*

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The high degree of overlap of race and poverty in our society has led to the presumption in both research and practice that ethnic disproportionality in special education is in large measure an artifact of the effects of poverty. This article explores relationships among race, poverty, and special education identification to arrive at a more precise estimate of the contribution of poverty to racial disparities. District-level data for all 295 school corporations in a midwestern state were analyzed for this study. Records included information on disability category, general and special education enrollment by race, socioeconomic level, local resources, and academic and social outcomes for 1 school year. Simple correlations among the variables demonstrate that correlations between race and poverty of even moderate strength do not guarantee that the 2 variables will function in the same way with respect to outcome variables, such as identification for special education services. Results of regression analyses indicate that poverty makes a weak and inconsistent contribution to the prediction of disproportionality across a number of disability categories. On the other hand, rates of suspension and expulsion consistently predict district rates of special education disproportionality. Inconsistent relationships between special education disproportionality and achievement may indicate a developmental trend in the systemic contribution to racial disparity. Ideal-type analyses examining race-poverty relationships indicate that where poverty makes any contribution above and beyond race in predicting disability identification, its primary effect is to magnify existing racial disparity.

The disproportionality of culturally and linguistically diverse students remains among the most significant and intransigent problems in the field of special education. Yet although the fact of ethnic disproportionality (see Note 1) in special education service has been extensively documented, the variables that cause and maintain these racial disparities have only recently begun to be explored (Couthino & Oswald, 2000; Losen & Orfield, 2002; National Research Council [NRC], 2002). One of the predominant explanations of special education disproportionality is the interaction of race and poverty. Given the unfortunate and high overlap of race and poverty in our society, it has been suggested that disproportionate minority referral to special education is linked less to race than to educational deficits among poor students of color that are created by socioeconomic disadvantage (MacMillan & Reschly, 1998). Others, however, have argued that a long history of school segregation means that poverty is in no way sufficient to explain minority disparities in special education (Losen & Orfield, 2002). This investigation analyzed data on ethnic disproportionality in special education from one midwestern

state to specifically focus on the extent to which poverty contributes to racial disparity.

Background

Since the issue was first identified (Dunn, 1968; Mercer, 1973), racial disparities in special education service have been the focus of influential litigation (*Larry P. v. Riles*, 1984; *PASE v. Hannon*, 1980), extensive exploration of test bias (Jensen, 1980; Reynolds & Brown, 1984; Valencia & Suzuki, 2001), and federal panels (Heller, Holtzmann, & Messick, 1982; NRC, 2002). Explorations of the extent of disproportionality at the national (Chinn & Hughes, 1987; Finn, 1982; Harry & Anderson, 1994; Oswald, Coutinho, & Best, 2002; Oswald, Coutinho, Best, & Singh, 1999; Parrish, 2002; Zhang & Katsiyannis, 2002) and state (Coulter, 1996; Ladner & Hammons, 2001; Skiba, Wu, Kohler, Chung, & Simmons, 2001) levels have consistently found the greatest disparities in the disability categories of mental retardation and emotional distur-

bance. Disproportionality has been most consistently documented for African American and Native American students and identified less consistently for Latino students. Despite consistent documentation of the existence of disproportionality, there has been relatively little exploration of the possible causes and factors contributing to racial disparities in special education (NRC, 2002).

The Overlap of Race and Poverty

Among the predominant explanations offered for the existence of disproportionate ethnic representation in special education is the influence of poverty or socioeconomic disadvantage on the academic readiness of minority students. Poverty was the focus of the first of four questions addressed in the recent report of the NRC, *Minority Students in Special and Gifted Education* (2002): whether there are “biological and social/contextual contributors to early development that differ by race and that leave students differentially prepared to meet the cognitive and behavioral demands of schooling” (p. 357). Based on its review, the NRC panel concluded with a “definitive yes” and suggested that the effects of a number of biological and social factors could be subsumed under the broader heading of poverty.

It is important to note that the NRC analyses did not directly address the relationship between poverty and special education disproportionality. Rather, the relationship between poverty and disproportionality in special education was assumed from the strength of the relationship between poverty and risk for school failure. Framed as it is in a study of minority representation in special education, however, one must assume that the NRC’s conclusion that sociodemographic disadvantage contributes to a lack of academic preparedness was meant to imply that such economic disadvantage also makes a key contribution to racial disparities in special education identification.

Indeed, the consistent overlap of race and poverty in this country has led some to suggest that race is simply a “proxy” for poverty. Arguing for the primacy of economic status in predicting educational outcomes, Hodgkinson (1995) suggested that poverty be used as a substitute for race in collecting demographic data. MacMillan and Reschly (1998) argued that insufficient attention has been paid to variations in special education disproportionality by social class:

We are willing to argue that in such a matrix, the intercorrelation between ethnicity and social class would be moderately high and that social class, and not ethnicity, would explain more variance in the rates of detection for these high-incidence disabilities, particularly MMR. (p. 20)

This view is also widely shared among school personnel (see, e.g., Allington & McGill-Franzen, 1997; Harry, Klingner,

Sturges, & Moore, 2002; Skiba, Simmons, Ritter, Kohler, & Wu, in press). In a qualitative investigation exploring the perceptions of school personnel concerning disproportionality and special education referral, Skiba et al. reported that the feelings of many respondents were summarized by one special education director: “I am not sure that what we say is disproportionality of race is not more disproportionality based on poverty.”

Assumptions Concerning the Influence of Poverty on Disproportionality

Thus, the assumption that disadvantages associated with poverty constitute a key or primary contribution to minority overplacement in special education is widely held in both research and practice. Yet there is a great deal to unpack in the logic of equating race and poverty to explain racial disparities in special education. There are at least four assumptions implicit in a logical sequence linking poverty and disproportionality:

1. Minority students are disproportionately poor and hence are more likely to be exposed to a variety of sociodemographic stressors associated with poverty.
2. Factors associated with living in poverty leave children less developmentally ready for schooling and ultimately yield negative academic and behavioral outcomes.
3. Students who are low achieving or at risk for negative behavioral outcomes are more likely to be referred to, and ultimately found eligible for, special education service.
4. Therefore, poverty is an important contributing factor that increases the risk, presumably in a linear fashion, of special education placement for minority students.

Given such a logical sequence, it might be assumed that if we prove the first three propositions, we can infer the last. Yet the absence of perfect correlations in the social sciences means that simply connecting a series of proven propositions will not be sufficient to prove other, untested relationships. Thus, even a relatively substantial overlap between poverty, race, and achievement does not guarantee a strong association between poverty and minority placement in special education. Stated differently, poverty could theoretically account for a relatively small proportion of minority overrepresentation, even in the face of substantial overlap between race, poverty, and achievement. The typical low to moderate level of correlation in the social sciences means that all assumptions, including the direct link between poverty and ethnic disproportionality in special education, must be tested directly.

Data on the Links Between Poverty and Disproportionality

There is in fact a fair amount of data and research available on each of the four prior assumptions, some of which appears to support a race–poverty connection in explaining disproportionality. There is, for example, a fairly strongly documented connection between minority status and poverty. According to the U.S. Bureau of the Census (2001), 14.4% of White children lived in homes at or below the poverty line in 2000, whereas 30.4% of African American children and 29.2% of Latino children lived in families below the poverty level.

As one moves through the remaining assumptions, however, the relationships between race, poverty, and educational outcomes become increasingly complex. Although socioeconomic disadvantage clearly significantly reduces school readiness (Duncan & Brooks-Gunn, 1997; McLoyd, 1998; NRC, 2002), direct links between poverty and academic and behavioral outcomes are not as impressive; for example, the impact of poverty on school completion is typically significant but small, while correlations with emotional and behavioral outcomes are at best inconsistent (Brooks-Gunn & Duncan, 1997). Nor do academic deficits necessarily predict special education referral. Although special education eligibility requires the demonstration of deficits in “a child’s educational performance” (Individuals with Disabilities Education Act [IDEA], 1997), the specific disability definitions of IDEA are intended to ensure that not all students with academic deficits or emotional-behavioral problems are eligible for special education. Thus, to prove that poverty contributes significantly to special education disproportionality, it would be necessary to show that economic disadvantage increases the risk not merely of underachievement but also of the specific types of learning and behavior problems defined by IDEA as disability.

Given this complexity, it is not surprising that investigations directly studying the impact of poverty on special education disproportionality have yielded inconsistent results that sometimes contradict the race–poverty hypothesis. Some investigations have found that poverty indeed creates higher rates of minority placement in the disability categories of learning disabilities (LD; Coutinho, Oswald, & Best, 2002), mental retardation (MR; Finn, 1982), and emotional disturbance (ED; Oswald et al., 2002). Others, however, have reported an opposite direction of effect, finding that as levels of poverty *decrease*, minority students are at greater risk for referral as LD (Zhang & Katsiyannis, 2002), MR (Oswald, Coutinho, Best, & Nguyen, 2001), and ED (Oswald et al., 1999). Finally, the actual distribution of racial disparities across populations and disability categories seems to contradict expectations based on the race–poverty hypothesis. Given that poverty is also widespread among Latino students, the finding of inconsistent Latino disproportionality fails to support a poverty causation; likewise, an explanation based on poverty has a difficult time

accounting for the finding that disproportionality is greater in the judgmental disability categories (e.g., LD, MR, ED) than in the more biologically based “hard” disability categories (e.g., visual or hearing impairment; Losen & Orfield, 2002).

Thus, although both scholarly treatments (MacMillan & Reschly, 1998; NRC, 2002) and local perspectives (Allington & McGill-Franzen, 1997; Skiba et al., in press) have tended to place a great deal of weight on the disadvantages created by poverty in explaining racial disparities in special education placement, the true relationship between poverty and disproportionality appears to be far more complex. The purpose of this study is to explore the impact of a variety of sociodemographic and poverty-related variables on levels of ethnic disproportionality in special education. This exploration involves using ordinary least squares (OLS) analysis to estimate the impact of poverty, among other variables, on minority overrepresentation in several disability categories. Then we use a logistic approach to illustrate the nature of the relationship between race and poverty in predicting special education disability identification.

Method

Sample

District-level data on general and special education enrollment in disability category by race, socioeconomic level, local resources, and academic and social outcomes were drawn from three separate statewide data sets in a midwestern state for the 2000–2001 school year. Data on disability categories for each of the state’s 295 school districts were drawn from the *Uniform Ethnic and Racial Questionnaire* and the *Uniform Federal Placement Questionnaire* (Section E: “Race/Ethnicity of Children with Disabilities Ages 6–21 by Educational Environment”) collected by the Indiana Department of Education Division of Exceptional Learners as part of its reporting requirements under Part B of IDEA 1997. This investigation was focused on disproportionality for African American students for two reasons: First, disproportionate identification and service are most consistent and severe for African American students across all disability categories (NRC, 2002), and second, statewide representation of other minorities has not been high enough in the target state to permit accurate assessment of disproportionality across a number of categories and settings.

Measures of Disproportionality

In recent years, the field of special education has begun to coalesce around two promising descriptive measures for describing the extent of disproportionality. The *composition index* (NRC, 2002) compares the proportion of students in special education from a given ethnic group with the proportion of that group in the population or in school enrollment. Thus, at

the national level, African American students account for 33% of students identified as mentally retarded but for only 17% of the student population (NRC, 2002). The *relative risk ratio* (Hosp & Reschly, 2003; Parrish, 2002) compares the rate at which different groups are served in special education to generate a ratio describing the extent of disparity. Thus, 2.64% of all African American students are identified as mentally retarded, as opposed to 1.18% of White students, meaning that African Americans are 2.24 times as likely as White students to be identified as mentally retarded (Fierros & Conroy, 2002). There appear to be advantages and disadvantages to both measures. With the composition index, it becomes difficult to find disproportionality when applying the measure to extremely homogeneous (e.g., above 90% of one ethnic group) populations (Westat, 2003). Although the risk ratio is less sensitive to changes in relative proportions of population, risk ratio estimates may become unstable in the case of small samples (Hosp & Reschly, 2004).

In addition, whether a measure is suitable for descriptive purposes may be independent of whether it can function as a dependent variable in an inferential statistical analysis. Odds and risk ratios by definition are not normally distributed and require transformation to meet the assumptions of inferential statistics (Hosp & Reschly, 2003). To ensure a normal distribution for purposes of OLS regression analysis in this investigation, the extent of disproportionality in each school corporation for each disability category and placement category was expressed as a two-sample z score for proportions (Skiba et al., 2001) for dependent samples. The z score standardizes the difference between the observed proportion of a given group in special education and that group's expected placement proportion given its proportion among nonstudents with disabilities (see Note 2). Thus, z scores describing the extent of district disproportionality of African American students in identification served as the dependent variable in a series of OLS regression analyses described below. A dichotomous variable representing identification or nonidentification (1 or 0, respectively) in disability categories served as the dependent variable in a series of logistic regression analyses, described below as well.

Research Design

We tested the influence of race, poverty, and other sociodemographic variables on special education disproportionality and identification in two related analyses. The first used OLS regression to predict disproportionality in specific disability categories. The second set of analyses employed logistic regression to assess the independent effects of race, poverty, and district-level resources and outcomes on the odds of special education identification.

Dependent Variables. The dependent variable in the OLS was the estimate of district-level disproportionality as expressed by the z score. In the logistic regression analysis,

the dependent variable was odds of disability identification. In both analyses, the five disability categories examined were mild mental retardation (MMR), moderate mental retardation (MoMR), emotional disturbance (ED), learning disability (LD), and speech and language (SL). The disability categories chosen for analysis were those that showed the highest levels of disproportionality in state-level data (Skiba et al., 2001).

Independent Variables. Independent variables were entered representing poverty level, district resources, and academic and behavioral outcomes. Race (African American or other) was implicit in the z score disproportionality measure in the OLS analyses but was entered explicitly as an independent variable in the logistic analyses. Two of the categories of variables selected, poverty and district resources, are roughly analogous to the first and second of the three questions considered by the NRC (2002): effects of poverty and effects of schooling (see Note 3).

Poverty Level. The percentage of children receiving free lunch was used as an index of level of economic disadvantage. Eligibility for the National School Lunch Program is a widely used indicator of student poverty because it is based on family income. At the school level, the percentage of students eligible for free or reduced-price lunches is a more accurate measure of a school's level of need than is general community income (FCC 97-157 ¶ 509). By inference, then, it is appropriate to include in a corporation-level model the percentage of students eligible for free or reduced-price lunches in the school corporation.

For the OLS equations, FREE LUNCH was entered as a continuous variable. To facilitate the calculation and interpretation of odds ratios, a design set of variables for free lunch was created for the logistic regression equations by dividing the sample into thirds based on the distribution of the free-lunch variable. The middle third, where the percentage of students eligible for free or reduced-price lunches ranged from 30% to 70%, served as the comparison group.

School Resources and Learning Environment. Poverty does not affect only individual school readiness. Community poverty also reduces the resources available to schools in that community (McLoyd, 1998). Thus, several measures of school resources were also studied:

- average teacher salary (SALARY)
- student-to-teacher ratio (STUDENT/TEACHER)
- expenditures per student (EXPEND)
- percentage African Americans at the district level (DIST % AFR AMER)
- size of school district (DIST ENROLL)

Previous investigations have noted the importance of system-level variables in predicting special education placement (Finn,

1982; Ladner & Hammons, 2001; NRC, 2002; Oswald et al., 2002; Zhang & Katsiyannis, 2002). Percentage African American enrollment and school district size were included explicitly in the logistic analysis only, as they are implicitly controlled for in the z score used in the OLS analyses.

Academic and Behavioral Outcomes. Both academic and behavioral deficits play a key role in referral to special education and could well contribute to disproportionality. Thus, we included in the model three academic achievement measures and two behavioral outcomes:

- mean third-grade score on state's accountability measure (ACCOUNTABILITY)
- average SAT scores (SAT)
- percentage of students in the district taking the SAT (SAT_PCT)
- overall school district suspension–expulsion rate (SUSPENSION)
- school district dropout rate (DROPOUT)

Achievement measures were intended to represent both early and late achievement. The third-grade accountability scores reflect students' academic abilities early in their educational progression. Grade 3 is the first year in which students take this state-mandated, criterion-referenced test. At the time of this study, more advanced versions of the test were administered in Grades 6, 8, and 10. Scores represented a composite of skills in English/language arts and mathematics. High school SAT scores provide a cumulative measure of achievement that reflects both student capability and school contributions. To control for the fact that average test scores decline as more students within the population of interest take the test (Powell & Steelman, 1996), we included the percentage of students taking the SAT as a variable in the model. Finally, as a measure of district behavioral outcomes, we included the district suspension–expulsion incidence rate (see Note 4) and district dropout rate.

Research Questions and Data Analyses

Two research questions guided our analyses.

Research Question 1: To what extent do poverty (as measured by free-lunch status), district resources, and academic–behavioral measures account for ethnic disproportionality in special education? To estimate the impact of poverty and other factors on disproportionality, the standardized rate of African American disproportionality for each of the disability categories was regressed on the predictor variables (see Note 5). Thus, the OLS regression explores the strength of contribution of a variety of variables on the extent of disproportionality in school districts.

Research Question 2: What are the relative contributions of race, poverty, school resources, and academic–

behavioral outcomes to the probability of diagnosis in special education? In particular, how do race and poverty influence that prediction? While Research Question 1 explores the degree to which variables influence the degree of disproportionality at the school district level, Question 2 more directly explores the impact of race (vs. other possible explanations) on special education identification rates. To estimate the impact of these variables on disability identification, logistic regression weighted by frequencies was performed (see Note 6).

Follow-Up Analyses. Two additional analyses followed the estimation of the logistic equations. Odds ratios drawn from the logistic regression equations were examined in a four-step process. The first step examined the odds of identification considering only race. The second step involved the calculation of odds ratios when only poverty was considered. In the third step, odds of identification were calculated when race and poverty were concurrently considered. The final step considered the full model.

Finally, to more precisely specify the contribution made by poverty to the estimation of disproportionality, ideal type analyses examined the likelihood of African American diagnosis in each of the special education categories at three hypothesized district income levels. Ideal type analyses can be used effectively to summarize the effects of key variables (in this case, race and poverty) on the dependent variable. In this type of analysis, one defines combinations of characteristics that correspond to ideal types in the population (Long, 1997). For our purposes, we created hypothetical students based on combinations of the independent variables. Specifically, we posited African American and non–African American students in three district environments—poor, middle income, and rich—while all other variables were held constant (e.g., at their means). Predicted probabilities of identification were calculated for each hypothetical situation. This allowed us to examine the influence of race on identification under different levels of poverty.

Results

Descriptive Data

Table 1 presents the simple correlations among race, poverty, achievement, and special education placement for school districts in this sample. As predicted by MacMillan and Reschly (1998), the relationship between poverty and race is moderately high ($r = .535$). Yet this moderately high correlation does not guarantee that poverty and race will operate in the same way in relationship to other variables. The rate of students receiving free lunch in a school district is also a moderately high predictor of both early school achievement (ACCOUNTABILITY) and late school achievement (SAT). Correlations between percentage African American enrollment and both

TABLE 1. Bivariate Relationships Among Key Variables

	DIST % AFR AMER	FREE LUNCH	ACCOUNTABILITY	SAT	% SPECIAL ED
DIST % AFR AMER	1.00				
FREE LUNCH	0.535*	1.00			
ACCOUNTABILITY	-0.336*	-0.574*	1.00		
SAT	-0.220*	-0.459*	0.400*	1.00	
% SPECIAL ED	0.057	0.318*	-0.284*	-0.158*	1.00

Note. DIST % AFR AMER = percentage African Americans at the district level; SAT = average SAT scores; % SPECIAL ED = district rate of enrollment in special education.
* $p < .01$.

measures of academic achievement are substantially lower, however. More telling is that while poverty shows a moderate correlation with district rate of special education placement, the correlation between rate of African American enrollment and special education placement in this state is effectively zero.

OLS Regression: Variables Contributing to Disproportionality

Disability. The weighted OLS regression results are presented in Table 2 (see Note 7). In general, they suggest that determinants of disproportionality are not uniform across disability categories.

Across analyses, poverty proved in general to be a weak and inconsistent predictor of disproportionality. A corporation's level of poverty does not significantly predict overall levels of disproportionality, nor does it enter the equation as a significant predictor of disproportionality for overall special education enrollment, ED, or MoMR. Results for SL and LD show a significant *inverse* relationship between free-lunch status and disproportionality: As the proportion of children in a corporation receiving free or reduced-price lunch increases, disproportionality in the disability categories of LD and SL decreases ($t = -2.18, p < .030$, and $t = -8.68, p < .00001$, respectively). The only disability category for which higher rates of poverty predict increased disproportionality is MMR ($t = 7.27, p < .00001$).

District suspension-expulsion rates were consistently associated with rates of ethnic disproportionality in special education. In fact, of all of the variables included in these analyses, only the suspension-expulsion rate at the district level proved a consistent predictor of ethnic disproportionality across disability categories (see Table 2). Suspension/expulsion rates were significantly and positively related to disproportionality in ED ($t = 3.21, p < .002$), MoMR ($t = 13.13, p < .002$), MMR ($t = 1.99, p < .05$), and LD ($t = 3.15, p < .002$).

Findings related to the other explanatory variables were inconsistent across disability categories. Disproportionality in

MoMR was found to be significantly and *negatively* related to a corporation's dropout rate ($t = -3.13, p < .002$), while disproportionality in SL was *positively* related to district dropout rate ($t = 5.06, p < .00001$). Achievement was found to be a significant predictor in two equations. A corporation's average SAT score was *positively* and significantly related to MMR disproportionality ($t = 4.96, p < .00001$) but inversely related to SL disproportionality ($t = -5.45, p < .00001$). Finally, districts with higher student-teacher ratios tended to have higher rates of African American disproportionality in MMR ($t = 2.67, p < .008$).

Logistic Regression: The Influence of Race and Sociodemographics

Given that poverty was found to be a weak and an inconsistent predictor of disproportionality in the OLS regression, a series of logistic analyses was conducted to explore the influence of the contributions of race, poverty, and a district's resources and learning environment in explaining the odds of special education identification.

In the logistic analyses (see Table 3), both poverty and race proved to be significant predictors of identification. The school resource, academic, and behavioral variables also proved to be significant, but less consistently so. It should be noted that the large sample size resulting from the weighting procedure increases the likelihood of statistical significance for all independent variables. Thus, the more important analyses are the exploration of odds ratios and the ideal type analyses.

A four-step analysis of odds ratios associated with the logistic analyses is presented in Table 4. When considering only race (step 1), African American students were more than 3 times as likely as other students to be identified as MMR ($z = 70.76, p < .0001$; see Note 8), nearly 2 times as likely as other students to be identified as MoMR ($z = 14.95, p < .0001$), and more than 2 times as likely as other students to be identified as ED ($z = 26.09, p < .0001$). Conversely, African American students were only .6 times as likely as other students to be identified as SL ($z = -24.80, p < .0001$) and .87 times as

TABLE 2. Weighted OLS Results: Predictors of Disproportionality in Special Education

Variables	ED		MMR		MoMR		LD		SL	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
CONSTANT	-9.337	5.679	-65.825**	11.635	-6.875	4.613	-7.576	4.725	27.750**	5.560
FREE LUNCH	-0.004	0.025	0.373**	0.051	-0.020	0.020	-0.046*	0.021	-0.213**	0.025
STUDENT/TEACHER	0.081	0.115	0.631**	0.236	0.074	0.093	0.130	0.096	-0.088	0.113
SALARY	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EXPERIENCE	-0.022	0.047	-0.166	0.097	-0.036	0.038	-0.018	0.039	0.016	0.046
EXPEND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ACCOUNTABILITY	-0.034	0.049	0.000	0.100	0.018	0.039	0.037	0.040	0.066	0.048
SAT	0.007	0.005	0.047**	0.010	0.007	0.004	0.001	0.004	-0.025**	0.005
SAT_PCT	0.004	0.016	-0.015	0.033	-0.013	0.013	0.006	0.013	-0.023	0.016
SUSPENSION	0.084**	0.026	0.103*	0.054	0.125**	0.021	0.069**	0.022	-0.037	0.026
DROPOUT	0.091	0.144	-0.458	0.297	-0.361**	0.115	0.012	0.121	0.717**	0.142
<i>N</i>	234		241	241	225	241	241	241	241	241
<i>R</i> ²	0.110		0.460	0.460	0.240	0.510	0.150	0.510	0.510	0.510
Adjusted <i>R</i> ²	0.070		0.440	0.440	0.200	0.490	0.110	0.490	0.490	0.490

Note. Equations are weighted by district enrollment, * $p < .05$; ** $p < .01$.

TABLE 3. Logistic Regression Predicting Identification in Disability Category

Variables	ED		MMR		MoMR		LD		SL	
	<i>b</i>	<i>SE</i>								
RACE	0.273**	0.038	0.944**	0.024	0.213**	0.055	-0.021	0.017	-0.488**	0.025
FLUNCH_RICH	-0.139*	0.043	-0.300**	0.027	-0.065	0.059	-0.051**	0.013	-0.050**	0.016
FLUNCH_POOR	0.235**	0.040	0.130**	0.025	0.279**	0.055	0.069**	0.013	-0.002	0.017
STUDENT/TEACHER	-0.076**	0.009	-0.042**	0.006	0.032**	0.012	-0.021**	0.003	-0.035**	0.004
SALARY	0.000*	0.000	0	0	0.000	0.000	0.000*	0.000	0.000**	0
EXPERIENCE	-0.007	0.005	0.003	0.003	-0.010	0.007	-0.002	0.001	0.001	0.002
EXPEND	0.000**	0.000	0.000**	0	0.000	0.000	0.000*	0.000	0	0
ACCOUNTABILITY	0.000	0.004	-0.012**	0.001	0.001	0.005	-0.009**	0.001	-0.003	0.002
SAT	0.000	0.000	-0.002**	0	-0.002**	0.000	0.000*	0.000	0	0
SAT_PCT	-0.001	0.001	-0.004**	0.001	-0.006**	0.002	0.000	0.000	0.001	0
SUSPENSION	0.002	0.002	-0.001	0.001	0.011**	0.002	0.002	0.001	-0.001	0.001
DROPOUT	0.055**	0.010	-0.020*	0.007	0.046*	0.014	-0.010*	0.004	0.030**	0.005
DIST ENROLL	0.000	0.000	0.000**	0	0.000**	0.000	0.000**	0.000	0.000**	0
DIST % AFR AMER	0.553**	0.125	-0.316**	0.08	-0.365	0.174	-1.063**	0.056	0.076	0.16

Note: FLUNCH_RICH and FLUNCH_POOR are the upper and lower categories respectively of a three-level division of the continuous variable, rate of students eligible for free lunch (FREE LUNCH). All other variable abbreviations are described in the text.

* $p < .01$. ** $p < .001$.

TABLE 4. Odds of Identification in a Multi-Step Process^a

	MMR	ED	MoMR	SL	LD
Step 1: Race					
RACE	3.36	2.16	1.88	0.60	0.87
Pseudo R^{2b}	(.024)	(.007)	(.004)	(.002)	(.001)
Step 2: Poverty^c					
FLUNCH_RICH	0.44	0.49	0.55	0.97	0.91
FLUNCH_POOR	2.12	2.08	1.94	0.99	1.09
Pseudo R^2	(.024)	(.011)	(.010)	(.001)	(.001)
Step 3: Poverty and Raced					
RACE	2.69	1.67	1.48	0.58	0.82
FLUNCH_RICH	0.67	0.77	0.92	0.93	0.94
FLUNCH_POOR	1.33	1.61	1.27	1.03	1.09
Pseudo R^2	(.031)	(.014)	(.011)	(.002)	(.001)
Step 4: Full Model^e					
RACE	2.57	1.31	1.24	0.61	0.98
FLUNCH_RICH	0.74	0.87	0.94	0.95	0.95
FLUNCH_POOR	1.14	1.27	1.32	1.00	1.07
ENR_TEACH	0.96	0.93	1.03	0.97	0.98
SALARY	1.00	1.00	1.00	1.00	1.00
EXPERIENCE	1.00	0.99	0.99	1.00	1.00
EXPEND	1.00	1.00	1.00	1.00	1.00
ACCOUNTABILITY TEST	1.00	1.00	1.00	1.00	0.99
SAT	1.00	1.00	1.00	1.00	1.00
SAT_PCT	1.00	1.00	0.99	1.00	1.00
SUSPENSION	1.00	1.00	1.01	1.00	1.00
DROPOUT	1.00	1.06	1.05	1.03	0.99
ENROLL	1.00	1.00	1.00	1.00	1.00
PCT_MINORITY	0.73	1.74	0.69	1.08	0.35
Pseudo R^2	(.025)	(.017)	(.012)	(.002)	(.002)

^aOdds were calculated based on the logistic equations (see Table 3). ^bPseudo R^2 is a measure of goodness of fit of the logistic regression equation, defined as $(1 - L1)/L0$, where $L0$ represents the log likelihood for the "constant-only" model and $L1$ is the log likelihood for the model with constant and predictors. A pseudo R^2 has been calculated for each step of the model as well as for the final model. ^cThe odds for each poverty category were calculated separately and are only grouped together for presentation, i.e. the odds were calculated based not on an equation that included both *flunch_rich* and *flunch_poor* but on separate equations for each poverty indicator. ^dThis step examines the odds of identification when poverty is controlled; thus, both *flunch_rich* and *flunch_poor* are simultaneously entered into the equation. ^eIn step four, district-level controls were added. The purpose of this step is not to interpret the change in odds for the control variables. Since these variables are continuous, a unit change in the variables would not be expected to dramatically affect the odds of identification. Rather, this step was taken in order to assess the impact of race and poverty on the odds of identification when other contextual factors were held constant.

likely as other students to be identified as LD ($z = -10.21$, $p < .0001$).

Poverty also influences the odds of identification when considered independent of race (step 2). For example, students living in a high-poverty school corporation were more than twice as likely as students in wealthier school corpora-

tions to be identified as MMR ($z = 46.81$, $p < .0001$), nearly twice as likely as students in wealthier school corporations to be identified as MoMR ($z = 19.08$, $p < .0001$), and twice as likely as students in wealthier school corporations to be identified as ED ($z = 28.79$, $p < .0001$). Students in school corporations with smaller proportions of students eligible for free

or reduced-price lunches were less than half as likely as students in school corporations with higher levels of poverty to be identified as MMR ($z = -39.85, p < .0001$), about half as likely as students in school corporations with higher levels of poverty to be identified as MoMR ($z = -14.18, p < .0001$) and ED ($z = -22.37, p < .0001$), and .91 times as likely as students in school corporations with higher levels of poverty to be identified as LD ($z = -9.99, p < .0001$).

When both race and poverty are entered simultaneously (step 3), both have independent effects on the odds of identification of special education disability; that is, race continues to significantly influence the odds of special education service when the effect of poverty is held constant. Controlling for poverty, African American students were more than 2.5 times as likely as other students to be identified as MMR ($z = 53.83, p < .0001$), about 1.5 times as likely as other students to be identified as MoMR ($z = 8.76, p < .0001$), and more than 1.5 times as likely as other students to be identified as ED ($z = 16.46, p < .0001$). At the same time, African American students were only about half as likely as other students to be identified as SL ($z = -25.71, p < .0001$) and .8 times as likely as other students to be identified as LD ($z = -13.83, p < .0001$) when level of poverty is controlled. Finally, it should be noted that when both race and poverty are considered simultaneously in this step, comparison of the odds ratios indicates that race is more predictive of special education identification than low income across all disability categories.

Inclusion of the district resource and academic-behavioral outcome variables (step 4) does not erase the fact that African American students have greater odds than their peers of diagnosis with MMR, 2.57 ($z = 40.89, p < .0001$); MoMR, 1.24 ($z = 4.70, p < .0001$); and ED, 1.31 ($z = 7.11, p < .0001$). Similarly, when the full model is considered, African American students are slightly more than half as likely as other students to be identified as SL ($z = -19.73, p < .0001$). Race does not significantly influence the odds of identification as LD when the full model is considered.

The results illustrate that although poverty and other sociodemographic variables entered into the model do influence identification, they in no way erase the impact of race. In fact, there is some indication of a mutual influence of both race and poverty in these data. The inclusion of poverty, district resource, and academic-behavioral outcome variables reduces the odds of an African American student being identified as mildly mentally retarded from 3.36 in the first step to 2.57 in the full model. Yet race and other variables also affect the influence of poverty, reducing the odds of MMR identification from 2.12 when considering only high poverty alone to 1.14 when all other variables are also considered.

Ideal Type Analyses

Influence of Race and Poverty. Because both race and poverty appear to predict special education disability identification, ideal type analyses were used to more precisely define the relationships among these variables. Figure 1 shows

the probability of disability identification for an African American student as compared to his or her peers at three district income levels—low income (70% and higher free or reduced-price lunch), mid-level (30%–70% free or reduced-price lunch), and high income (0%–30% free or reduced-price lunch)—when all other demographic variables are held constant in the equation. The convergence of the two lines representing African American and other students graphically represents the nature of the relationship of poverty and race in predicting placement. Two lines that overlapped completely would demonstrate that poverty completely accounts for the influence of race on placement. Parallel lines showing a trend indicate that poverty has little effect: The size of racial disparities remains constant across levels of poverty; that is, race and poverty are independent contributors to the likelihood of placement. Lines that diverge indicate that the effect of poverty on racial disparity changes depending on the level of poverty. Finally, increasing trend lines suggest a relationship in the expected direction, whereas decreasing trend lines suggest that poverty *decreases* the likelihood of special education services.

These figures illustrate that, *at all economic levels*, African Americans are disproportionately represented in special education disability categories. The nature of the relationship between race and poverty varies considerably, however. Poverty seems to have a differential effect on LD and SL, with rates of service increasing with increased poverty for SL and decreasing with increased poverty for LD. Yet for both LD and SL, the magnitude of racial discrepancies remains constant regardless of level of poverty, all else being equal: In both LD and SL, African Americans are underserved regardless of economic level. Thus, for these disability categories, although poverty affects overall level of service, it appears to have little effect above and beyond race in predicting disproportionality.

In the MMR, MoMR, and ED analyses, poverty acts to reinforce disparities created by race, all else being equal. Thus, while racial disparities in service remain evident at all levels of poverty, increased poverty magnifies the discrepancy between rates of service for African American versus other children in the categories MMR, MoMR, and ED.

In sum, the relationships among race, poverty status, and special education disability identification appear to be extremely complex. For all disability categories, racial disparities are in evidence across all levels of poverty. In some cases, poverty has little to no effect on the size of the racial discrepancy in special education services. In other cases, increased poverty appears to magnify the size of the racial disparity in special education.

Discussion

The view that ethnic disproportionality in special education is due in large measure to the impact of poverty is prominently represented among researchers (MacMillan & Reschly, 1998; NRC, 2002) and practitioners (Skiba et al., in press). Yet these

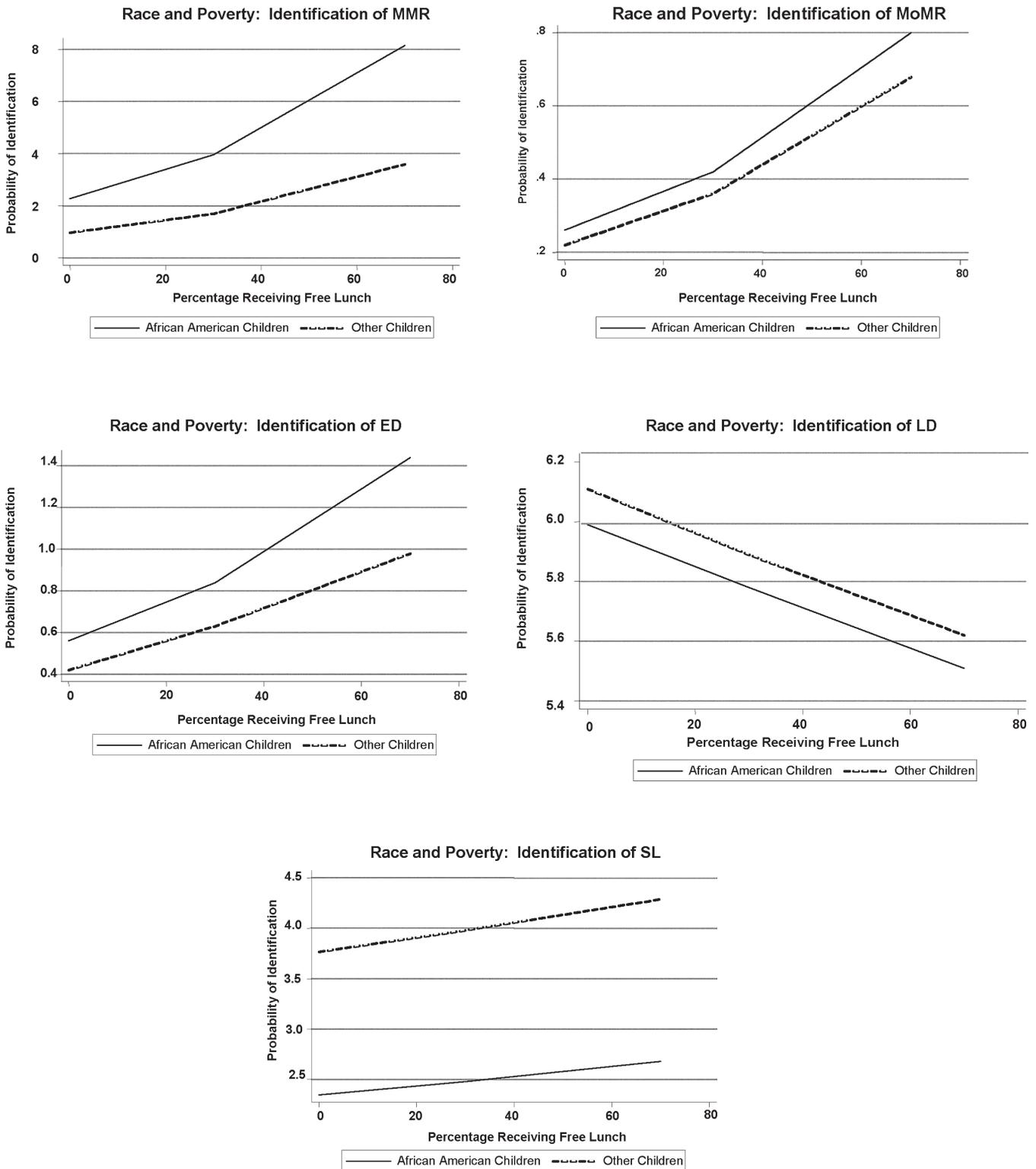


FIGURE 1. Graphical representation of the relationship between poverty and special education identification for African Americans versus other children. The y axis represents the probability of identification. The x axis represents the percentage of children receiving free lunch in a school district. The figures illustrate that the relationship between poverty and identification differs for African American children versus other children and is not uniform across disability categories.

results join other recent results in suggesting that relationships among poverty, race, achievement, and special education eligibility are complex and often counterintuitive.

In order for race to serve as a proxy variable for poverty (Hodgkinson, 1995; MacMillan & Reschly, 1998), poverty would need to account nearly entirely for the variance due to race in predicting the variable of interest—in this case, minority overrepresentation. Simple correlations among race, poverty, academic outcomes, and special education placement rates presented in this study are certainly significant. Yet even a moderately strong correlation between race and poverty does not mean that those two variables will act the same way in relation to a third variable. Thus, while poverty in these data shows a moderately strong correlation with measures of academic achievement and special education placement rates, the correlation between percentage of African American enrollment and academic achievement is much lower, and the correlation between race and special education rates is virtually zero.

Thus, it is not surprising that poverty does not fully explain ethnic disproportionality in multivariate analyses; indeed, poverty proved in general to be a weak and inconsistent predictor of disproportionality. In only one of the disability categories tested in the multiple regression analyses (mild mental retardation) did increased poverty predict increased disproportionality. In two categories (emotional disturbance and moderate mental retardation) poverty failed to enter the equation, and in two others (learning disability and speech and language) it entered in a direction counter to expectations: Richer districts tend to have *higher rates* of ethnic disproportionality in learning disabilities and speech and language. Finally, logistic analyses—in particular, multistep analysis of odds ratios—showed that when race and poverty are considered simultaneously, knowledge of race appears to be a more important predictor of special education identification than knowledge of poverty status.

These results are both consistent and inconsistent with previous research. The finding that poverty is associated with increased racial disparity in mild mental retardation is consistent with the findings of Finn (1982). At the same time, it runs counter to the finding by Oswald et al. (2001) that the odds of minority student placement in the MMR category *decreased* as poverty increased. In a broader sense, however, these results must be seen as consistent with a body of literature that has failed to establish any reliable relationship between rates of poverty and disproportionate placement in special education.

The complexity of the relationship between race and poverty in predicting disproportionality is graphically illustrated in ideal type analyses. In some cases, poverty has no effect on the size of racial disparities; in others, it magnifies the effect of race. Although there is a significant disparity in special education service by race for all disability categories, higher levels of poverty were found to widen racial disparities in the areas of mild mental retardation, moderate mental retardation, and emotional disturbance. Perhaps the most accurate summary of these data might be that in those cases

where poverty makes any contribution to explaining disproportionality, its effect is primarily to magnify already existing racial disparities.

A particular difficulty with the predominant focus on poverty is that it may well obscure the consideration of other variables that make a contribution to ethnic disproportionality. The “predisposition to blame families for children’s learning and behavioral difficulties” (Harry et al., 2002, pp. 78–79) has been widely documented in studies of perceptions of educators and policymakers (Allington & McGill-Franzen, 1997; Harry et al., 2002; Skiba et al., in press). It has been argued that this emphasis on individual socioeconomic disadvantage serves to distract attention from continuing structural inequalities in education that serve to replicate disadvantage in our society (Sleeter, 1995; Valencia, 1997).

In this study, one such structural variable, district rate of school suspension and expulsion, proved to be the most robust predictor of special education disproportionality. Racial and ethnic disparities in school discipline have been widely and consistently documented (Children’s Defense Fund, 1975; Costenbader & Markson, 1998; Gregory, 1997; Kaeser, 1979; Massachusetts Advocacy Center, 1986; McFadden, Marsh, Price, & Hwang, 1992; Nichols, Ludwin, & Iadicola, 1999; Raffaele-Mendez & Knoff, 2003; Skiba, Michael, Nardo, & Peterson, 2002; Wu, Pink, Crain, & Moles, 1982). A relationship between racial or ethnic disparities in discipline and special education referral may be further evidence of a general inability on the part of schools to accommodate cultural differences in behavior, particularly for African American students (Hosp & Hosp, 2002; Townsend, 2000). Or it may simply be that poorer, predominantly minority districts have fewer resources for handling both learning and behavior problems in the classroom and thus refer more students from the classroom for both discipline and special education service (see, e.g., Gerber & Semmel, 1984). Clearly, however, racial and economic disparities in opportunity to learn in general education have been so widely identified that the absence of studies directly investigating the impact of resource discrepancies on special education referral must be regarded as puzzling.

Two possible limitations of the current investigation should be noted. First, the data come from a single midwestern state. Although the levels of disproportionality in that state seem roughly commensurate with national rates of disproportionality (Skiba et al., 2001), further demonstrations from other states would be valuable to ensure that the data used in this study are not somehow idiosyncratic with respect to these variables. In general, geographic variability in racial disparity is an area of research well worth exploring: Given regional differences in diversity, one would expect some regional variation in patterns of, and reasons for, ethnic disproportionality in special education.

Second, as in previous investigations (Ladner & Hammons, 2001; Oswald et al., 1999), the data in this investigation were based not on individual observations of race, placement, and economic status but on rates of those variables at the dis-

strict level. It is possible that district averages for these variables will over- or underestimate the actual overlap of race and poverty. One might expect that analyses using individually based poverty estimates could provide a more precise assessment of the contribution of poverty to racial disparity in special education service.

Yet, on the other hand, such concerns may represent a technical question that fails to account for the broader historical and contextual factors contributing to racial disparities in education. Even if it were possible to demonstrate statistically that individual poverty status completely accounted for the variance previously attributed to race in special education disproportionality, that demonstration would still be insufficient to disentangle the fundamental complexity of race, poverty, and special education referral. Clearly, students living in poverty begin school with disadvantages that diminish educational readiness. As McLoyd (1998) noted, however, those same students typically attend schools with dramatically reduced educational resources and fewer opportunities for quality instruction. Thus, any index of individual poverty collected after school entry must be viewed as an inherently confounded measure, reflecting the influence not only of the biological and social stressors associated with early childhood poverty, but also of restricted educational opportunities for disadvantaged students attending resource-poor schools. In an educational system in which poor students of color routinely receive an inferior education, it would require a longitudinal study beginning from before school entry and probably continuing through secondary school to parse the unique contributions of race and poverty to educational disadvantage.

In sum, the relationships among race or ethnicity, poverty, and the disproportionate placement of minority students in special education are highly complex, and their directionality often defies expectation. These data are consistent with previous investigations in suggesting that poverty is only one part, and perhaps not a very central part, of a complex of factors predicting African American overrepresentation in special education. Those contributing factors also appear to include systemic variables, such as level of district resources and perhaps even disciplinary philosophy. Finally, the continued significance of race as a predictor of special education disability identification regardless of controls for a variety of other variables leads us to agree with those who contend that the process of special education referral and identification remains to some extent discriminatory (Ladner & Hammons, 2001; Losen & Orfield, 2002). To better understand and especially address the causes of ethnic disproportionality, it is critical that efforts continue to be made to identify both the individual *and* the systemic factors that create and maintain educational inequity.

NOTES

1. The term *minority disproportionality* (or *minority overrepresentation*) is more widely used in the literature on disproportionate representation. Yet it is common that the overrepresentation in certain disability categories of students of color is typically ac-

companied by *underrepresentation* in those same categories among White students (see, e.g., National Research Council, 2002). The term *ethnic disproportionality* is thus used in this article to reflect the fact that the issue does not affect solely minority students but rather reflects a disproportionate distribution across a number of ethnic groups, including White students.

2. The specific test used is the two-sample z test for dependent samples. The formula in this case is

$$Z = P_1 - P_2 / \text{Standard Error}$$

where P_1 is the sample proportion of African Americans among a disability category and P_2 is the sample proportion of African American students not identified as disabled in the school corporation. The standard error for this equation is the standard error of the sampling distribution of difference of two dependent proportions:

$$SE = \sqrt{(P_1(1 - P_1)/n_1) + (P_2(1 - P_2)/n_2) - (2r_{12} / (\sqrt{P_1(1 - P_1)/n_1} + \sqrt{P_2(1 - P_2)/n_2}))}$$

where P is the proportion of general enrollment represented by African Americans, n_1 is the total number of students in a disability category, and n_2 is the total number of nonstudents with disabilities in a school corporation. Positive z scores indicate overrepresentation, while negative z scores indicate underrepresentation. It can be shown that the chi-square statistic is simply the square of the two-sample z test for proportions. A more complete discussion and derivation of this methodology can be found in Skiba et al. (2001).

3. The third category of influence on placement decisions, the special education identification and referral process itself, is examined in a related paper (Skiba et al., in press).
4. Due to the way in which the state under investigation collects data on suspensions and expulsions, data represent incidence rates (the total number of suspensions and expulsions), not the number of children suspended or expelled. In other words, if corporation A has 10 children who have been expelled three times each, the incidence rate for that corporation would be 30.
5. Because the z score is a continuous variable, ordinary least squares (OLS) regression was the most appropriate statistical tool. To account for the statistical discrepancies associated with differences in size across corporations, we weighted the regression by corporation enrollment. The regression equation is expressed as

$$Y_{\text{DISPROPORTIONALITY}} = a + B_{\text{FREE LUNCH}} + B_{\text{EXPEND}} + B_{\text{STUDENT/TEACHER}} + B_{\text{SALARY}} + B_{\text{ACCOUNTABILITY}} + B_{\text{SAT}} + B_{\% \text{SAT}} + B_{\text{DROPOUT}} + B_{\text{SUSPENSION}}$$

For variables involving placement, language involving over- and underrepresentation can become somewhat counterintuitive. For a general education class placement, the z test is actually measuring the degree of overrepresentation of African Americans in a less restrictive setting. Because, however, African American students are in general *underrepresented* in less restrictive settings, we take the liberty of reversing signs on regression coefficients and discussing findings in terms of the underrepresentation of African Americans in general education classrooms.

6. Four different weighted categories were constructed based on district-level demographics: African American and disabled, African American and nondisabled, non-African American and disabled, and non-African American and nondisabled. The outcome variable was expressed as a dichotomous variable where 1 repre-

sented service in the disability category and 0 represented no service. Race (African American, coded as 1; non-African American coded as 0) was entered as a predictor variable. All other predictor variables remained the same as in the OLS equation, with the addition of size of district enrollment (DIST ENROLL) and the percentage minority in the district (DIST % AFR AMER) resulting in the following equation:

$$Y_{\text{DISABLED}} (1 = \text{yes}; 0 = \text{no}) = a + B_{\text{FREE LUNCH_POOR}} + B_{\text{FREE LUNCH_RICH}} + B_{\text{EXPEND}} + B_{\text{STUDENT/TEACHER}} + B_{\text{SALARY}} + B_{\text{ACCOUNTABILITY}} + B_{\text{SAT}} + B_{\% \text{SAT}} + B_{\text{DROPOUT}} + B_{\text{SUSPENSION}} + B_{\text{RACE}} + B_{\text{DIST ENROLL}} + B_{\text{DIST \% AFR AMER}}$$

7. The actual N of cases in each equation differed slightly. In order for disproportionality to be calculated and thus a dependent variable to be available, there had to be African Americans in the school corporation and children identified in the disability category. The exact N of cases for each equation can be found in Table 2.
8. Note that in this instance, the z does not refer to the z score as used for the dependent variable in the OLS equations. The z test used in logistic regression is analogous to a t test used in OLS regression, providing a measure of the significance of the contribution of a single variable to the logistic equation. For more on the use of the z test in logistic equation, refer to Long (1997, pp. 85–88).

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