

Disentangling the Roles of Institutional and Individual Poverty in the Identification of Gifted Students

Rashea Hamilton
D. Betsy McCoach
M. Shane Tutwiler
Del Siegle
E. Jean Gubbins
Carolyn M. Callahan
Annalissa V. Brodersen
Rachel U. Mun

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Abstract

Although the relationships between family income and student identification for gifted programming are well documented, less is known about how school and district wealth are related to student identification. To examine the effects of institutional and individual poverty on student identification, we conducted a series of three-level regression models. Students of poverty are generally less likely to be identified for gifted services, even after controlling for prior math and reading achievement. Further, school poverty predicts the percentage of gifted students identified in a school. Within-districts, even after controlling for reading and math scores, the poorer schools in a district have lower identification rates. Whereas students of poverty are generally less likely to be identified for gifted services, poor students in poor schools are even less likely to be identified as gifted.

Introduction

Student Poverty and Gifted Identification

The underrepresentation of low-income students in gifted education is a persistent problem (Borland, Schnur, & Wright, 2000; Sparks, 2015). According to current data, on average, 51% of students in public schools come from low-income backgrounds (Suitts, 2015) but no published research provides a definitive national estimate for the specific proportion of low-income students identified as gifted. However, research suggests that the proportion of low-income students in gifted education classrooms does not reflect their proportion in general student enrollment (Carman & Taylor, 2010; Siegle et al., 2016). In one study, students from low-income backgrounds were five times less likely to participate in gifted programming than their higher income peers (Borland, 2005).

At least three factors may contribute to this disproportionate representation. First, gifted programs commonly utilize a referral-based system of student nomination that may be biased against low-income students (McBee, Peters, & Miller, 2016). In a referral-based system, students are first nominated by teachers or parents and then evaluated for eligibility for gifted programming with nationally normed standardized tests (Putallaz, Baldwin, & Selph, 2005). However, nomination rates vary based on socioeconomic status. In an examination of one state's screening process, McBee (2006) found that students who were eligible for free and reduced-price lunch (FRL) were far less likely to be nominated than their full-price lunch peers: non-FRL students received more than 3 times the number of teacher referrals when compared to FRL students. Yoon and Gentry (2009) suggest that teachers may, in part, rely on their own middle-class values to define giftedness. Thus, their conceptions of gifted behaviors may not align with the behaviors low-income gifted students display, resulting in lower rates of nominations.

Second, low-income students tend to have fewer opportunities to learn when compared to their higher-income peers, which may explain disproportionately low rates of identification for low-income students (Peters & Enggerand, 2016). The impact of family poverty on student achievement is well documented. For a variety of reasons including limited word exposure (Hart & Risley, 2003), limited parental spending (Kornrich & Furstenberg, 2013), limited access to learning materials (Mason & McCormick, 1986; Neuman & Celano, 2006; Neuman, Celano, Greco, & Shue, 2001), and limited time for academically-oriented activities (Adams, 1990), low-income students tend to have fewer opportunities to develop academic skills (Peters & Enggerand, 2016), especially outside of school. Thus, many children from low-income families begin their academic experience with fewer skills than their higher-income counterparts and often remain on a path of low performance (Alexander, Entwisle, & Horsey, 1997; Denton & West, 2002; Duncan, Brooks-Gunn, & Klebanov, 1994; Hauser-Cram, Sirin, & Stipek, 2003).

Lastly, low-income students tend to earn lower scores on assessments of academic achievement and cognitive ability than higher SES students (A. W. Gottfried, A. E. Gottfried, Bathurst, Guerin, & Parramore, 2003; Larson, Russ, Nelson, Olson, & Halfon, 2015; Lohman, 2005). Plucker, Hardesty, and Burroughs (2013) documented excellence gaps, or disparities in high levels of performance between multiple groups, including low-income and high-income students. The math and reading scores from the National Assessment of Educational Progress (NAEP) indicated vast disparities between FRL eligible and non-FRL eligible students in terms of the percentage of students who achieve advanced math and reading scores (Plucker et al., 2013). These gaps have continued to widen since 2006 (Plucker et al., 2013). The disparities by income also exist for standardized tests of cognitive ability. Kaya, Stough, and Juntune (2016)

examined income-based differences on the Otis-Lennon School Ability Test and found that FRL status was associated with lower verbal intelligence and achievement scores.

Scholars have investigated the relationship between limited income at the family level and gifted identification in prior studies but no published research examines the role of district and school poverty in gifted identification. Despite a lack of direct evidence of the negative influence of school and district poverty on gifted identification, a wealth of evidence suggests these processes might be related.

School and District Poverty

Although the relationship between school and district SES and gifted identification has not been investigated, the relationship between school SES and school achievement is well established (McCoach & Colbert, 2010; McCoach et al., 2010). The school environment, specifically factors related to school finances and the proportion of impoverished students the school serves, can influence student outcomes, even after controlling for family and neighborhood influences (Esposito, 1999; Van Zandt & Wunneburger, 2011). Puma (1999) found that school poverty was associated with low test scores, and this trend appeared to continue over time. Similarly, Perry and McConney (2010) found that students, regardless of students' family income, demonstrated lower achievement in schools characterized as low income. Higher values of school SES were associated with higher values of student achievement (Perry & McConney, 2010). Van Zandt and Wunneburger (2011) researched the effects of residential segregation on the achievement of low-income students in urban settings. Disadvantaged students who attended schools with small proportions of other economically disadvantaged students performed better on state assessments than those who attended schools with high proportions of economically disadvantaged students. Schwartz (2012; cited in Owens, Reardon, & Jencks, 2016a) reported similar findings; public housing students attending low-poverty schools earned higher math and reading scores than public housing students in high-poverty schools.

A variety of factors may explain why schools with greater poverty are associated with lower student outcomes. These include lower teacher expectations (Jussim & Eccles, 1992; Jussim, Eccles, & Madon, 1996), peer effects (Lin, 2010; Mashburn, Justice, Downer, & Pianta, 2009), and mundane curriculum (Schmidt, Cogan, Houang, & McKnight, 2009). Further, schools serving primarily poor students experience difficulty recruiting and retaining effective teachers with prior experience (Mangiante, 2011), and a disproportionate number of under-qualified and inexperienced teachers tend to be placed in low-income schools (Darling-Hammond, 2004; Krei, 1998).

Clearly, one of the most important factors is limited resources. Some scholars suggest that high poverty schools' limited resources are a function of inequitable distribution practices at the district level due, in part, to the dependence of school funding on local tax revenue (Owens, Reardon, & Jencks, 2016b). Although state and federal funding can supplement funding in schools located in poor neighborhoods, in many states, schools are still largely dependent on local residents' property and income taxes to fund school budgets (Baker & Corcoran, 2012).

The limited resources of impoverished schools can impact school programming emphasis as well as achievement. Brent, Roellke, and Monk (1997) examined New York State schools' funding data and found a disproportionate allocation of resources for programming based on school wealth. Whereas poor schools received a disproportionate amount of funding for remedial programming and no funding for advanced programming, wealthier schools received a

disproportionate amount of funding for advanced programming and no funding for remedial programming (Brent et al., 1997). Similarly, Raudenbush, Fotiu, and Cheong (1998) found that wealthier schools were more likely to offer advanced math courses to students than poor schools.

Inequitable school funding can also impact the availability of gifted programming. In fact, Baker (2001b) reports that opportunities for gifted students vary extensively and are related to local funding levels and socioeconomic status. Although some state policies mandate identification of and service to gifted students, most of the decisions about funding and resources take place at the district level (Kettler, Russell, & Puryear, 2015). The proportion of economically disadvantaged students within a school was one of the primary determinants of gifted-related resource allocation; poor schools allocated fewer fiscal and human resources to gifted programming (Kettler et al., 2015). Similarly, Baker (2001a) found that districts that did not allocate any funding for gifted programming had 12% or more FRL eligible students than districts that did allocate funding to such programming.

In conclusion, evidence suggests that poverty at the student, school, and district levels can negatively influence student outcomes, and students from low-income backgrounds also face individual barriers to identification for gifted services. However, there is a lack of research that examines the connections between both individual and institutional poverty and gifted identification. To address this gap, we seek to answer four research questions:

1. What is the probability of being identified as gifted? How do rates of identification vary for low-income students after controlling for achievement?
2. What is the extent of *within-district* and *between-district* variability in the proportion of students who are identified as gifted and who are identified as low income?
3. What is the relationship between school poverty and school identification rates? To what degree do school identification rates vary *within-* and *between-districts*?
4. To what extent do school poverty and school achievement explain *between school* variability in gifted identification rates?
- 5.

Method

Sample

Three waves of student-level data were collected from three state departments of education. Each state's education policy requires the identification of gifted students, though specific identification criteria vary both across and within states and across local education agencies within those states. Data from a cohort of students who entered 3rd grade in 2011 and finished 5th grade in 2014 were analyzed in this study. The distribution of the sample of students is presented in Table 1. For school- and district-level data, student data were aggregated by the school and district in which students were enrolled at 4th grade. School and district datasets were further supplemented with data from the 2013-2014 National Center for Educational Statistics' (NCES) Elementary/Secondary Information Systems (ELSI).

Measures

Free and reduced-price lunch (FRL). FRL served as a proxy for income with student eligibility for FRL treated as a dichotomous variable in which 0 represented students who were not FRL eligible and 1 represented students who were eligible. Further, individual students were considered eligible for FRL if they were eligible at any point during the 3-year time period of the study. At the school and district levels, FRL was a continuous variable and reflected the proportion of students in the school/district eligible for FRL. In States 1 and 2, the proportion of

FRL eligible students in schools and districts were aggregated from the total school population (not just the cohort used in the analyses). State 3 did not provide us with this information directly. Therefore, we used demographic data provided by the ELSI.

Gifted identification. At the student level, being identified as gifted by 5th grade was a dichotomous variable (coded 0 or 1) in which 0 represented students who were not identified as gifted by 5th grade, and 1 represented students who were identified as gifted by 5th grade. At the school and district levels, gifted identification was a continuous variable that represented a school or district proportion of students identified as gifted by 5th grade. At the school and district levels, these data were aggregated from the student cohort.

Achievement. At the student level, achievement was a continuous variable that represented students' achievement score on each state's math and reading tests in 3rd grade. To predict students' gifted identification status by fall of 5th grade, we utilized students' end of 3rd grade reading and math scores. At the school and district levels, achievement scores were aggregated from the student level by school or district, respectively. Table 2 contains descriptive statistics for student, school, and district achievement scores. Because scales for each state's achievement tests were different and gifted education policies varied by state, data were analyzed separately by state.

Analysis

Descriptive analysis. To examine the underrepresentation of students of poverty in programs for the gifted, we first conducted a series of descriptive analyses, using cross-tabulations of the frequencies of students who were gifted/not and FRL eligible/not. In addition, we examined means on variables of interest, including achievement. Finally, we examined the simple bivariate correlations among reading and math achievement, school FRL, and the school percentage of gifted students at the school level. For any of the analyses examining the percentage of schools that had no identified gifted students (no gifted/FRL students), we removed any schools with less than 10 total students in the cohort from our analyses. Schools with very small numbers of students in the cohort might not be expected to have any gifted students within a given cohort. Therefore, eliminating small schools from these sub-analyses provided a more accurate representation of the phenomenon.

Multilevel analysis. To examine the student-, school- and district-level influences on the probability of being identified as gifted, we conducted a series of three- and two-level regression models using the *gllamm* package in *Stata 14*. Multilevel modeling takes into account the clustered nature of the data, results in more appropriate standard error estimates, and allows researchers to ask and answer nuanced questions about interactions that occur across the multiple levels of analysis (McCoach, 2010; McCoach & Adelson, 2010; Raudenbush & Bryk, 2002; Raudenbush, Bryk, Cheong, Congdon, & Du Toit, 2011). Part of the goal in utilizing multilevel analysis is to understand how students, schools, districts vary in respect to a particular outcome variable (in the three-level models, the outcome variable of interest is students' gifted status; in the two-level models, the outcome variable of interest is schools' percentage of students identified as gifted). Further, we are interested in what variables help explain that variance. Multilevel modeling allows us to deconstruct that variance by level. In the three-level regression models, variance is examined at the student level (level 1), school level (*within-district*; level 2), and the district level (*between-district*; level 3). In the two-level regression models, variance is examined at the school level (*within-district*; level 1), and the district level (*between-district*; level 2).

Three-level regression models. At level 1, we included four student variables: FRL eligibility, gifted identification status (the outcome variable), reading achievement, and math achievement. Achievement scores were grand mean centered; dichotomous variables were dummy coded and added to the model uncentered. At level 2, we included four school-level variables: the school percentage of FRL eligible students, the percentage of students identified as gifted at 5th grade, schools' average reading achievement, and schools' average math achievement. All continuous variables were grand-mean centered at level 2. At level 3, we included five district-level variables: the percentage of FRL eligible students, percentage of students identified as gifted at 5th grade, districts' average reading achievement, districts' average math achievement, and districts' percentage of underrepresented students. Again, all continuous variables were grand-mean centered. The equation for the full three-level model is presented in Figure 1.

Two-level regression models. To examine the role of school- and district-level factors in the proportion of students identified as gifted, we conducted a separate series of two-level regression models. For these models, the percentage of identified gifted students in the school became the outcome variable. At level 1, we included school-level variables: school percentage of FRL eligible students, schools' average reading achievement, and schools' average math achievement. All variables were group-mean centered at level 1. At level 2, we included district-level variables: the district percentage of FRL eligible students, the district percentage of students identified as gifted at grade 5, districts' average reading achievement, districts' average math achievement. All level 2 variables were grand-mean centered. The equation for the full two-level model is presented in Figure 2.

Results

What is the probability of being identified as gifted and how do rates vary for low-income students?

Descriptive Analyses

State 1. Approximately 18.8% of students in the cohort were identified as gifted by 5th grade. In addition, 61% of the students in the cohort were eligible for FRL at some point during the 3rd, 4th, or 5th grades. The proportion of students identified as gifted differed radically across FRL eligible and non-FRL eligible groups. Approximately 9% of the FRL eligible students were identified as gifted in State 1. In contrast, over 34% of the non-FRL eligible students were identified as gifted. In other words, the probability of being identified as gifted was almost 4 times higher (Relative Risk [RR]=3.82) for students who had never been eligible for FRL as it was for students who had ever been eligible for FRL. Table 3 contains the frequencies of gifted and FRL eligible students for State 1.

FRL eligible students were far less likely to be identified as gifted than non-FRL eligible students. If FRL eligibility and gifted identification were independent, then we would expect 11% of students to be both gifted and FRL eligible and 7% of students to be gifted and non-FRL eligible. Only 5.5% of students in the cohort from State 1 were both gifted and FRL eligible, which is half as many students as would be expected. In contrast over 13% of students in the sample were identified as gifted but had never received FRL, which is nearly twice as many as would be expected if FRL status and gifted status were unrelated. Moreover, there were almost 2.5 times as many gifted students who were not FRL eligible students as there were gifted

students who were FRL eligible, even though FRL students composed over 60% of the sample. The odds of being identified as gifted were over 5 times greater (Odds Ratio [OR]=5.29) for students who had never been eligible for FRL than for students who had ever been eligible for FRL.

Recall that in State 1, over 18% of the students in the sample were identified as gifted at some point during elementary school. Despite the state mandate requiring identification for gifted programming, approximately 3% of the schools ($n=39$) had no identified gifted students in the grade level cohort. These schools were overwhelmingly schools with high numbers of FRL eligible students. We refer to these as the “0 gifted schools.” These 0 gifted schools were generally much poorer than the other schools in the state. These schools averaged 85.87% students who were FRL eligible, compared to the overall average of 61%. In addition, their average reading and math achievement scores were at least one standard deviation lower than school math and reading scores in the reference group. Further, there were 86 schools (6.6%) in the sample that had no FRL eligible students identified as gifted in the cohort. Although these schools tended to have a smaller percentage of FRL eligible students overall (mean=47.37%), the lower percentage of FRL eligible students was not low enough to explain the lack of gifted/FRL students in the cohort. Overall, these “no gifted FRL” schools tended to have higher than average achievement. They also exhibited higher achievement gaps between the FRL and non-FRL eligible students than either the 0 gifted schools or the “reference” schools. Table 4 contains the descriptive statistics, broken out by school type. Note that almost 10% of the schools in State 1 contained no gifted FRL students for the cohort that we examined.

Next, we divided schools into seven groups based on the percentage of FRL eligible students in the school identified as gifted. Table 5 contains these results. Given that 18% of the students in the state were identified as gifted, if the proportions of gifted students were relatively evenly divided across schools and FRL eligible students were identified as frequently as non-FRL students, most schools in the state should identify at least 10% or 15% of their FRL eligible students as gifted. Although over 18% of students in the cohort were identified as gifted overall, only 5% of the schools ($n=66$) identified at least 15% of the FRL eligible students in their school as gifted. Another 12% of the schools ($n=158$) identified 10%-15% of the FRL students in their schools as gifted. In other words, only 17% of the schools in the state identified at least 10% of the FRL students as gifted. Approximately 83% of the schools in the state identified fewer than 10% of FRL students as gifted; over 50% of the schools identified fewer than 5% of the FRL students as gifted; and over 20% of the schools identified fewer than 2% of the FRL students in the school as gifted.

State 2. Approximately 10.3% of students in the cohort were identified as gifted by 5th grade. In addition, 51% of the students in the cohort were eligible for FRL at some point during the 3rd, 4th, or 5th grades. However, once again the proportion of students identified as gifted was dramatically different across the two groups. In State 2, approximately 6% of FRL eligible students were identified as gifted, whereas 14.5% of non-FRL eligible students were identified. Thus, the probability of being identified as gifted was over twice as high (RR=2.32) for students who had never been eligible for FRL as it was for students who had ever been eligible for FRL. Table 6 contains the frequencies of gifted and FRL eligible students for State 2.

If FRL eligibility and gifted identification were independent, then we could expect 5.3% of students to be both gifted and FRL eligible and 5% of the students to be gifted and non-FRL eligible. However, FRL eligible students were far less likely to be identified as gifted than non-FRL eligible students. Only 3.2% of students in the sample were both gifted and FRL eligible. In

contrast, 7.2% of students in the sample were identified as gifted but had never been eligible for FRL. In other words, there were over twice as many gifted students who were not FRL eligible students as there were gifted students who were FRL eligible. The odds of being identified as gifted was over 2.5 times greater (OR=2.55) for students who have never been eligible for FRL than for students who have ever been FRL eligible.

Recall that in State 2, over 10% of the students in the sample were identified as gifted at some point during elementary school. Despite the state mandate requiring identification for gifted programming, over 14% of the schools ($n=141$) had no identified gifted students in the grade level cohort. However, in contrast to State 1, these schools were not necessarily high poverty schools. Instead the school percentage of FRL students in this set of schools was 49%, which was slightly less than the average percentage of FRL eligible students statewide (51%). Further investigation into these schools revealed that a portion of these schools ($n=57$) were part of districts with separate schools for their gifted or high-achieving students. However, for the remaining 84 schools with no identified gifted students, the reason for the lack of identified gifted students was unclear.

Over 25% of the schools ($n=261$) in the sample had no FRL eligible students identified as gifted in the cohort. These schools tended to have a smaller percentage of FRL eligible students (mean=28.21%), and they tended to have higher than average achievement. Thus, only 59% of the schools in State 2 had at least one gifted student who was FRL, and 41% of schools had no FRL eligible students identified as gifted in the cohort.

Next, we divided schools into 6 groups based on the percentage of FRL eligible students in the school who were identified as gifted. Table 7 contains these results. Given over 10% of the students in the state were identified as gifted, if the proportions of gifted students were relatively evenly divided across schools and FRL eligible students were identified as frequently as non-FRL eligible students, most schools in the state should identify nearly 10% of their FRL students as gifted. Although over 10% of students in the state were identified as gifted overall, only 9% of the schools ($n=92$) identified at least 10% of the FRL eligible students in their school as gifted and 13% of schools identified at least 7.5% of the FRL students as gifted. In contrast, over 80% of the schools in the state identified fewer than 5% of the FRL eligible students as gifted and almost 60% of the schools in State 2 identified fewer than 2% of the FRL students in the cohort as gifted. Table 8 contains the descriptive statistics, broken out by school type.

State 3. Approximately 10.5% of students in the cohort were identified as gifted by 5th grade. In addition, 67% of the students in the cohort were FRL eligible at some point during the 3rd, 4th, or 5th grades. Once again, however, the proportion of students identified as gifted was dramatically different across the two groups. In State 3, over 18% of non-FRL eligible students were identified as gifted, whereas only 6.6% of FRL eligible students were identified as gifted. Thus, the probability of being identified as gifted was almost three times as high (RR=2.77) for students who had never been eligible for FRL as it was for students who had ever been eligible for FRL. Table 9 contains the frequencies of gifted and FRL eligible students for State 3.

If FRL eligibility and gifted identification were independent, then we could expect approximately 7% of students to be both identified as gifted and FRL eligible and 3.5% of students to be identified as gifted and non-FRL eligible. However, FRL eligible students were far less likely to be identified as gifted than non-FRL eligible students. Only 4.4% of students in the sample were both identified as gifted and FRL eligible. In contrast 6% of students in the sample were identified as gifted but had never been eligible for FRL. In other words, almost twice as many gifted students who were not FRL eligible were identified as gifted as would be expected

and nearly half as many FRL eligible students were identified as would be expected gifted if the two variables were independent. The odds of being identified as gifted was over 3 times greater (OR=3.17) for students who have never been eligible for FRL than for students who have ever been eligible for FRL.

Recall that in State 3, over 10% of the students in the sample were identified as gifted at some point during elementary school. Despite the state mandate requiring identification for gifted programming, almost 17% of the schools ($n=343$) had no identified gifted students in the grade level cohort. As was the case in State 1, these schools tended to have higher than average percentages of FRL students. The school percentage of FRL students in this set of schools was 83%, which was higher than the overall average of 67%. In addition, almost 10% of the schools ($n=201$) in the sample had no FRL eligible students identified as gifted in the cohort. These schools tended to have a smaller percentage of FRL eligible students (mean=53%), and they tended to have higher than average achievement. Thus, in the cohort that we examined, only 73.4% of the schools in State 3 had at least one gifted student who was eligible for FRL in the cohort that we examined; almost 27% of the schools had no FRL eligible students identified as gifted in the cohort. Table 10 contains the descriptive statistics, broken out by school type.

Again, we divided schools into six groups based on the percentage of FRL eligible students in the school identified as gifted. Table 11 contains these results. In State 3, Although over 10% of students in the cohort were identified as gifted overall, less than 22% of the schools ($n=441$) identified at least 10% of the FRL eligible students in their school as gifted. Approximately 55% of the schools in the state identified fewer than 5% of the FRL eligible students as gifted and over 34% of the schools in the state identified fewer than 2% of the FRL eligible students as gifted.

These descriptive results clearly demonstrated that FRL eligible students are less likely to be identified for gifted programs than non-FRL eligible students. However, FRL eligible students also tend to exhibit lower academic achievement than their peers. Thus, one plausible explanation for the descriptive results is that students of poverty are less likely to be identified as gifted because they perform more poorly on standardized achievement tests. Therefore, our next set of analyses examined the effect of FRL eligibility on identification as gifted, after controlling for prior reading and math achievement test scores.

Multilevel Analyses

To explore how student-, school-, and district-level factors were related to identification rates, we conducted a series of three-level models. First, we estimated the unconditional means model (Model 1) to determine what proportion of the variance in being identified as gifted lay at each of the three levels.

State 1. Utilizing a hierarchical linear probability model (Model 1), we found that approximately 2% of the variance was *between-districts*, 6% of the variance was between schools *within-districts*, and 92% of the variance was between students within schools. After adding students' eligibility for FRL to the model (Model 2), results implied the probability of being identified as gifted for non-FRL students was .32. In contrast, FRL eligible students were far less likely to be identified as gifted ($\gamma_{100}=-1.65$): Their model implied probability of being identified as gifted was only .08. These results are concordant with our descriptive analyses.

In Model 3, we controlled for reading and math achievement at the student, school, and district levels. We also controlled for the percentage of gifted students and the percentage of FRL students at the school and district levels. Additionally, we allowed the FRL slope to vary across

schools and districts. Even after controlling for achievement, the percentage of gifted students in the school (and district), and the percentage of FRL eligible students in the school (and district), students who were FRL eligible were less likely to be identified as gifted ($\gamma_{100} = -.61$). After controlling for prior achievement and school and district demographics, the odds of being identified as gifted were 1.85 times greater for non-FRL students than they were for FRL eligible students. For example, as presented in Figure 3, the model implied that the probability of being identified as gifted for a student whose math and reading scores were each 10 points (approximately one standard deviation on the state test) above the state mean in a school and district with average achievement, an average percentage of FRL eligible students, and an average percentage of gifted students was .68 for a non-FRL student but only .54 for an FRL eligible student. In other words, the probability of prototypical high-achieving students who were not FRL eligible being identified as gifted was 1.26 times greater than their FRL eligible peers, controlling for all other student, school, and district factors. In State 1, the student poverty slope on gifted varied across districts ($p < .001$) but not across schools. This indicates that the negative effect of FRL eligibility on gifted identification status varied across districts but it did not vary across schools *within-districts*. Table 12 contains the results of Model 3 for State 1.

State 2. To estimate the proportion of variance in gifted status that lay *between-districts*, between schools *within-districts*, and between students within schools, we estimated a random effects ANOVA model using a hierarchical linear model. In State 2, approximately 2% of the variance was *between-districts*, 8% of the variance was between schools *within-districts*, and 90% of the variance was between students within schools.

Next, we added students' eligibility for FRL to the model (Model 2). The overall estimated probability of being identified as gifted for non-FRL students was .10 ($\gamma_{000} = -2.25$). Students who were FRL eligible were less likely to be identified as gifted ($\gamma_{100} = -1.18$). The model implied probability of being identified as gifted for FRL students was .03. The odds that a non-FRL eligible student would be identified as gifted were 3.28 times larger than the odds for an FRL eligible student. Put another way, the probability of a prototypical student who was not FRL eligible being identified as gifted was 3.33 times greater than the probability of their FRL eligible peers, controlling for all other factors in the model.

In Model 3, we controlled for reading and math achievement at the student, school, and district level. We also controlled for the percentage of gifted students and the percentage of FRL students at the school and district levels. Again, the FRL slope was allowed to vary across schools and districts. Results demonstrated that even after controlling for achievement, the percentage of gifted students in the school (and district), and the percentage of FRL students in the school (and district), students who were eligible for FRL were less likely to be identified as gifted ($\gamma_{100} = -.30$). After controlling for prior math and reading achievement and school and district demographics, the odds of being identified as gifted were 1.35 times greater for non-FRL students than they were for FRL students. For example, as presented in Figure 4, the model implied that the probability of being identified as gifted for a student whose math and reading scores were each 100 points (just over one standard deviation on the state test) above the state mean in a school and district with average achievement, an average percentage of FRL eligible students, and an average percentage of gifted students was .44 for a non-FRL student but only .37 for an FRL student. In other words, the probability of being identified as gifted was 1.19 times greater for high-achieving non-FRL students versus their equally high-achieving FRL-eligible peers in the same types of schools and districts. Again, although the student poverty

slope did not vary across schools, the effect of student poverty on identification status did vary across districts ($p < .001$). Table 13 contains the results of Model 3 for State 2.

State 3. Utilizing a hierarchical linear probability model (Model 1), approximately 1% of the variance was *between-districts*, 9% of the variance was between schools *within-districts*, and 90% of the variance was between students within schools. After adding students' FRL eligibility to the model (Model 2), the results indicated the probability of being identified as gifted for non-FRL students was .09. In contrast, FRL eligible students were less likely to be identified as gifted ($\gamma_{100} = -1.00$): The model implied probability of being identified as gifted was only .03.

In Model 3, we again controlled for reading and math achievement at the student, school and district level. We also controlled for the percentage of gifted students and the percentage of FRL eligible students at the school and district levels. Additionally, the FRL slope was allowed to vary across schools and districts. Results demonstrated that students who were eligible for FRL were less likely to be identified as gifted ($\gamma_{100} = -.24$) even after controlling for achievement, the percentage of gifted students in the school (and district), and the percentage of FRL students in the school (and district). After controlling for prior achievement and school and district demographics, the odds of being identified as gifted were 1.27 times as large for non-FRL students as they were for FRL students. For example, as presented in Figure 5, the model implied that the probability of being identified as gifted for a non-FRL student whose math and reading scores were each 40 points (approximately two standard deviations) above the state mean in a school and district with average achievement, an average percentage of FRL eligible students, and an average percentage of gifted students was .70 for a non-FRL student but only .65 for an FRL student¹. That is to say, the probability of high-achieving non-FRL students being identified as gifted was 1.10 times greater than their FRL eligible peers in similar schools and districts. In State 3, the student poverty slope varied across both schools and districts ($p < .001$). This indicates that the effect of student poverty on identification varied both *within-* and *between-districts*. Table 14 contains the results of Model 3 for State 3.

What is the extent of *within-district* and *between-district* variability in the proportion of students who are identified as gifted and who are identified as low income?

Because districts set and implement specific policies related to gifted identification and services, one might assume that the proportion of students identified as gifted would be approximately equal across all schools in the district. If different schools within the same district identify similar percentages of gifted students but districts vary in terms of the percentage of students that they identify as gifted, then we would expect to observe large *between-district* variability and small *within-district* variability in terms of the school percentages of students identified as gifted. On the other hand, if schools within the same district vary widely in terms of the percentages of students that they identify as gifted, then we would expect to see large between school/*within-district* variance. Our prior results suggested that schools, even schools within the same district, appeared to vary widely in terms of the proportions of students identified as gifted. Far more of the variance in identification rates was between schools within the same district than *between-districts*. Therefore, to explicitly estimate the extent to which this variance was *within-districts* or *between-districts*, we estimated a two-level unconditional means model for each state in which we predicted the proportion of gifted students in the schools.

¹ State 3 utilizes a selection process that results in achievement scores being less predictive of gifted status than the other two states.

Across all three states, these results indicated that the vast majority of the variability in the proportion of students identified as gifted lies between schools *within-districts* and relatively little of the variability lies *between-districts*.

In State 1, schools varied greatly in terms of the percentage of students identified as gifted, even within the same district. For the cohort that we examined, the school average percentage of identified gifted students was 17%. However, the school mean identification rate varied a great deal across schools, even schools within the same district. The standard deviation for the school mean gifted identification rate was 12%, suggesting that some schools identified no gifted students whereas other schools identified high percentages of gifted students. Approximately 23% of the variance in schools' proportion of gifted students was *between-districts*, while 77% of the variance was between schools *within-districts*.

There was also a great deal of between school variability in the percentage of students identified as gifted at each school in State 2. For the cohort that we examined, the school average percentage of identified gifted students was approximately 10%. The standard deviation, however, for the school mean gifted identification rate was 11%, suggesting that some schools identified no gifted students whereas other schools identified high percentages of gifted students. In State 2, approximately 18% of the variance in schools' proportion of gifted students was *between-districts*, while 82% of the variance was between schools *within-districts*.

In State 3, we again observed a great deal of between school variability in the percentage of students identified as gifted at each school. For the cohort that we examined, the school average percentage of identified gifted students was approximately 10%. The standard deviation for the school mean gifted identification rate was 11%, suggesting that the proportion of students that schools identified for gifted services varied widely. Nine percent of the variance in school proportions of gifted students was *between-districts* and 91% of the variance was between schools *within-districts*.

Across all three states, schools within the same district vary widely in terms of the proportion of gifted students they identify/serve: over 75% of the variance in school identification rates was *within-district* in each of the three states. However, our descriptive results also suggested a great deal of *within-district* heterogeneity in terms of the school percentages of FRL eligible students. Across the three states, our results indicate that most of the variability in the proportions of students who are FRL-eligible lies between schools *within-districts* while relatively little lies *between-districts*. In State 1, approximately 21% of the variance in schools' proportion of low-income students was *between-districts* while 79% was *within-districts*. In State 2, 35% of the variance in schools' proportion of FRL eligible students was *between-districts*, while 65% was *within-districts*. Lastly, in State 3, 12% of the variance in schools' proportion of FRL eligible students was *between-districts*, while 88% was between schools *within-districts*. Therefore, schools within the same district vary widely in terms of the proportions of FRL eligible students they serve. This finding indicates that the demographic composition of the students who attend different schools within the same district is highly variable. Given that elementary schools are often neighborhood schools and neighborhoods are increasingly stratified by SES (Massey, Rothwell, & Domina, 2009), this is not necessarily a surprising finding; however, it is an important component for understanding the inter-relationships among student, school, and district poverty and gifted identification.

What is the relationship between school poverty and school identification rates?

School poverty was negatively related to school gifted identification rates in all three states. However, this negative relationship was especially pronounced in State 1. In State 1, the correlation between the percentage of FRL students in the school and the percentage of gifted students in the school was $-.65$. In State 2, the correlation between the percentage of FRL students in the school and the percentage of gifted students in the school was $-.31$. In State 3, the correlation between the percentage of FRL students in the school and the percentage of gifted students in the school was $-.42$. Tables 15, 16, and 17 contain the school level correlations among the percentage of gifted students, the percentage of FRL students, and the average reading and math scores for States 1, 2, and 3.

To what extent do school poverty and school achievement explain between school variability in gifted identification rates?

State 1. Recall that in State 1, the intra-class correlation coefficient, which captures the proportion of *between-district* variance to total variance, was $.28$. This suggests that 72% of the variance in identification rates lies between schools *within-districts* and only 28% lies *between-districts*. Put another way, there is over 2.5 times more *within-district* variability in identification rates than there is *between-district* variability. A great deal of this *within-district* variability can be explained by the percentage of FRL eligible students in the school. Adding the percentage of FRL students as a predictor (Model 1) explained approximately 55% of the *within-district* variability but only 4% of the *between-district* variability in schools' gifted identification rates.

However, across all three states, school math and reading achievement is negatively related to school poverty and positively related to the percentage of students in the school identified as gifted. Next, we added achievement to the model (Model 2) at the school and district levels. Even after controlling for school and district math and reading achievement, school proportion FRL negatively predicted the school proportion of identified gifted students ($\gamma_{10} = -.17$). This means that, given 2 schools with identical mean math and reading achievement, a 10% difference in school FRL, the percentage of gifted students in the school would be expected to differ by 1.7%. Adding school and district achievement to the model reduced *within-district* variability in school identification rates by an additional 7% (resulting in a 62% reduction over the null model) and *between-district* variability was reduced by an additional 7% (resulting in an overall reduction of 11% over the null model). Results for State 1 are presented in Table 18.

State 2. Recall that the intra-class correlation coefficient for State 2 was $.18$, suggesting that 82% of the variance in identification rates lies between schools *within-districts* and only 18% lies *between-districts*. A portion of this *within-district* variability can be explained by the percentage of FRL eligible students in the school. Adding the percentage of FRL eligible students as a predictor explained approximately 20% of the *within-district* variability but only 3% of the *between-district* variability in schools' gifted identification rates. Next, we added achievement to the model (Model 2) at the school and district levels. After controlling for school and district math and reading achievement, the school proportion of FRL students no longer negatively predicted the school proportion of identified gifted students ($\gamma_{10} = -.04$). However, after controlling for school and district math and reading achievement, the district proportion of FRL students negatively predicted the school proportion of identified gifted students ($\gamma_{10} = -.08$). In other words, given 2 districts with identical mean math and reading achievement, for each 10% difference in district FRL, the percentage of gifted students in the school would be expected to

differ by .8%. Including school and district achievement as well as school and district poverty explained approximately an additional 9% of the *within-district* variance resulting in an overall reduction of 29%, as compared to the null model. Adding achievement explained an additional 1% of the *between-district* variance, resulting in an overall variance reduction of 4% over the null model. Results for State 2 are presented in Table 19.

State 3. Recall that the intra-class correlation coefficient in State 3 was .09. This suggests that 91% of the variance in identification rates lies between schools *within-districts* and only 9% lies *between-districts*. This suggests that a great deal of this *within-district* variability can be explained by the percentage of FRL eligible students in the school. Adding the percentage of FRL eligible students as a predictor (Model 1) explained approximately 16.2% of the *within-district* variability but only 3.2% of the *between-district* variability in schools' gifted identification rates. Even after controlling for school and district math and reading achievement, the school proportion of FRL eligible students negatively predicted the school proportion of identified gifted students ($\gamma_{10}=-.03$), although the effect was smaller than in State 1. Given 2 schools with identical mean math and reading achievement, for each 10% positive difference in school FRL, the percentage of gifted students in the school would be expected to differ by .3%. Including school and district achievement as well as district poverty in the model (Model 2), *within-district* variability in school identification rates was reduced by an additional 12%, meaning that Model 3 explained 28% of the *within-district* variance as compared to the null model. The addition of school and district achievement did not explain any additional *between-district* variability in school identification rates. Results for State 3 are presented in Table 20.

Summary of Results

Overall, these results suggest that poverty, as measured by the school percentage of students who are eligible for FRL, is related to the school's gifted identification rate. In two of the three states (States 1 and 3), the school percentage of FRL students was a statistically significant predictor of the proportion of gifted students in the school, even after controlling for school and district reading and math achievement. In State 2, although the school percentage of FRL students did not predict the school percentage of gifted students, the proportion of FRL students in the district negatively predicted the proportion of gifted students in the school, even after controlling for district math and reading achievement. These findings suggest that both institutional poverty and individual poverty help to explain elements of underrepresentation of students in programs for the gifted.

Discussion

The results of this study illuminate both the institutional and individual relationship between poverty and the likelihood of a student being identified for gifted services. Even when they exhibit equally high mathematics and reading achievement, FRL students were less likely to be identified for gifted services than non-FRL students. Additionally, in two of the three states (States 1 and 3), higher poverty *schools* tended to have lower proportions of gifted students, even after accounting for school and district math and reading achievement. In the other state (State 2), higher poverty *districts* tended to have lower proportions of gifted students, even after accounting for school and district math and reading achievement. These results suggest that both individual and institutional (contextual) factors contribute to the poverty identification gap.

We began this inquiry with a broadly defined question: What is the relationship between poverty and gifted identification? The answer is in some ways predictable, and in others less-so.

Our findings are generally in line with past research, highlighting the negative relationship between poverty and students' identification as gifted (Borland et al., 2000; Sparks, 2015). Building upon the work of Borland et al., our research demonstrates that poverty (operationalized as FRL eligibility) reduces the likelihood of being identified as gifted, even after controlling for student prior math and reading achievement. Our methodology allowed us to go beyond marginal comparison of rates of identification by comparing students with identical achievement and demographic profiles, and the results were consistent: across the three states under study, students from low-income backgrounds (eligible for FRL) are less likely to be identified as gifted, even after controlling for prior achievement.

Manifold instructional and/or institutional factors, such as systematically lower expectations for various sub-groups of students (Jussim & Eccles, 1992; Jussim et al., 1996; Tenenbaum & Ruck, 2007) or the values that teachers hold (Yoon & Gentry, 2009) may be at play, though our observational data do not allow us to investigate such factors directly.

Generally, the proportion of students identified as gifted in a school appears to be higher in lower-poverty schools, and schools within the same district vary widely both in terms of the percentage of gifted students in the school and the school poverty level. Furthermore, school poverty and the school percentage of identified gifted students are negatively related to each other *within-districts* as well as *between-districts*. While demonstrably lower test scores in schools with a high percentage of FRL (e.g., Puma, 1999, Perry & McConney, 2010) certainly can account for some of this trend, both our student-level findings and our school-level findings point to a more direct link between poverty and gifted identification. Higher poverty schools tend to have lower percentages of identified gifted students, even after controlling for school and district achievement.

Even in states that mandate identification for gifted services, non-negligible numbers of schools failed to identify any students as gifted. In some cases, the lack of gifted students in certain schools within a district may be explained by the existence of a gifted magnet program where students move from their home school to a centralized school for gifted services. However, it does not appear that the existence of gifted magnet programs can explain most of the cases of schools without gifted students. In two of the three states, these schools had high percentages of FRL eligible students, thus reinforcing the finding that the characteristics of the local school have great influence on identification for gifted services.

In both the cases of poor schools identifying fewer gifted students and poor schools being more likely to have zero-gifted students, inequitable distribution of district resources may play a role. Although states may mandate the identification of and service to gifted students, most of the decisions about the funding and resources needed for schools to comply with these mandates take place at the district level. Research has shown that the proportion of economically disadvantaged students within a school was one of the primary determinants of gifted-related resource allocation in one state (Kettler et al., 2015). In another state, Brent et al. (1997) found the same trend of disproportionate allocation of resources for programming based on school wealth, with poor schools receiving disproportionately greater funding for remedial education than advanced programming. It could also be the case that the districts involved in the current study use school demographics to make funding-related decisions.

Another reason for under identification, despite similar levels of academic achievement, could be due to a lack of teacher awareness of gifted behaviors in low-income populations of students (McBee, 2006). Teacher nomination is often the first step in the process of being identified as gifted, and low-income students may display behaviors that do not align with what

teachers expect of gifted students. Yoon and Gentry (2009) suggest that teachers may, in part, rely on their own middle-class values to define giftedness, and this could impact rates of nomination and ultimately identification.

Additionally, district-level identification policies may contribute to the under identification of low-income students. Districts may utilize a district-based standard or norm to guide which students are eligible for gifted services. Using district-wide norms to identify students across schools, which themselves have different norms, leads to enormous variability in the percentages of students that are identified as gifted across the schools within the district. In such a scenario, it is possible that entire schools may not have students who meet the district criteria. Yet, within those schools, there are surely students who are well ahead of their peers and in need of additional intellectual challenge. Lohman (2005) advocates for the use of a relevant, local norming group to use in making comparisons and decisions about identification for gifted services. Such local norms would need to be computed at the school level rather than the district level to effectively address between-school inequities in poverty. School-based norms allow for the identification of top performing students at each school, with the goal of providing advanced programming suitable for their needs.

Implications

The implications of this research are clear: students who live in poverty are likely to be overlooked during the gifted identification process. Further, *within-district* inequities appear to contribute to the under-identification of students of poverty as gifted. High potential students of poverty are less likely to be recognized and served in programs for the gifted. Such inequities have the potential to increase, rather than decrease social inequities. Gifted education is certainly not the root of our social inequities. However, at present, it appears that gifted identification procedures may be perpetuating societal inequities rather than helping to eliminate them.

These findings have implications for both policy and practice as it relates to the identification of gifted students. First, districts might consider a resource allocation formula that ensures all high-potential students, regardless of their school context, can access gifted programming. Further, districts might consider utilizing school-based norms to guide identification decisions rather than district-based standards. School districts might also consider implementing universal screening programs. Card and Guiliano (2015) found that universal screening helped to increase the number of traditionally underserved students who were screened and identified for gifted services. To ensure that schools and districts are able to comply with gifted-related mandates, states should consider adopting policies that would help equitably distribute resources, especially to low-income schools.

Limitations

There are several limitations to the current study. First, we had access to data for only one cohort of students, those who were 5th graders in 2013-2014. Therefore, we do not know how the results might differ for other cohorts of students in the three states. In addition, our only measure of student and school poverty was FRL eligibility, which may not adequately capture the nuances of individual and institutional poverty. Having access to a more fine-grained measure of SES would certainly be preferable. Finally, we only examined results from three states. Given that each state has different definitions of gifted education, different regulations and statutes for gifted education identification, and different policies guiding the identification and service delivery for gifted students, the results in other states could certainly be quite

different. However, it is noteworthy that across all three states, we found a tendency for FRL students to be under-identified as gifted, even after controlling for math and reading scores and key school and district demographics.

Future Research

Nominations, selective screening, and teacher rating scales are elements of identification processes across many districts across the nation (Callahan, Moon, & Oh, 2013; National Association for Gifted Children [NAGC] & Council of State Directors of Programs for the Gifted [CSDPG], 2015). Future research should examine the relationship between nomination and identification policies and practices and gifted identification rates. Since district norms might inform the extent to which low-income students have access to gifted programming, future research should examine the efficacy and feasibility of integrating school norms into gifted identification procedures. Future research should also examine the ways in which poverty interacts with other demographic characteristics to impact identification. Although examining other demographic factors such as race and language proficiency were beyond the scope of the current study, research suggests that students who are low-income and/or from culturally and linguistically diverse communities might face particular challenges related to nomination and identification (Siegle et al., 2016). More empirical research is needed to investigate these issues further. Lastly, there is some evidence that professional development can help enhance identification rates of traditionally underrepresented populations (Esquerdo & Arreguín-Anderson, 2012). Future research should empirically test this hypothesis.

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Table 1
Distribution of Sample

	Students	Districts	Schools
State 1	98,764	114	1,318
State 2	63,323	180	1,034
State 3	168,444	73	2,194

Table 2
Mean Student, School, and District Achievement by State

	State 1	State 2	State 3
Student Math (SD)	346.47 (9.72)	463.90 (90.72)	204.24 (20.81)
School Math (SD)	345.95 (4.07)	464.56 (45.29)	202.08 (10.13)
District Math (SD)	345.61 (2.51)	465.69 (33.93)	204.11 (2.70)
Student Reading (SD)	440.14 (9.17)	562.25 (74.29)	203.58 (20.16)
School Reading (SD)	439.81 (3.61)	563.41 (34.90)	201.84 (9.64)
District Reading (SD)	439.60 (2.31)	563.65 (28.20)	203.47 (2.64)

Table 3

Frequencies of Students by Free and Reduced-price Lunch and Gifted Status in State 1

Gifted Status	FRL Eligibility		Total
	Not FRL	FRL	
Not Gifted	24,248	53,033	77,281
Gifted	12,631	5,227	17,858
Total	36,879	58,260	95,139

Table 4
Comparisons Among the Three Groups of Schools in State 1

Variable	Reference (<i>n</i> =1177)		No Gifted (<i>n</i> =39)		No Gifted FRL (<i>n</i> =86)	
	Mean	<i>SD</i>	Mean	<i>SD</i>	Mean	<i>SD</i>
School % FRL	61.33	21.85	85.87	13.16	47.37	25.24
School % Gifted	7.64	5.31	1.07	1.18	8.05	6.19
District % FRL	54.67	11.80	61.15	11.12	48.08	12.53
District % Gifted	15.50	5.54	10.68	3.84	15.97	7.55
Prop Gifted FRL in cohort	0.06	0.05	0.00	0.00	0.00	0.00
READ	445.79	3.66	441.89	3.95	447.54	3.94
MATH	449.78	3.92	445.69	4.02	450.90	4.32
Reading Gap (by FRL)	5.80	3.64	4.32	6.64	7.08	3.41
Math Gap (by FRL)	5.39	3.65	4.41	5.88	7.15	3.35

Table 5

Breakdown of Schools by Percentage of Students by Free and Reduced-price Lunch Status Identified as Gifted in State 1

	<i>n</i>	%	% FRL
No GT students	39	3%	85.87
Less than 2% GT FRL	240	18%	48.24
2-5% GT/FRL	399	31%	58.45
5-7.5% GT FRL	244	19%	61.72
7.5-10% GT FRL	156	12%	63.18
10%-15% GT FRL	158	12%	71.92
15%+ GT FRL	66	5%	78.07

Table 6

Frequencies of Students by Free and Reduced-price Lunch and Gifted Status in State 2

Gifted Status	FRL Eligibility		Total
	Not FRL	FRL	
Not Gifted	29,558	33,155	62,713
Gifted	5,016	2,209	7,225
Total	34,574	35,364	69,938

Table 7

Breakdown of Schools by Percentage of Students by Free and Reduced-price Lunch Status and Identified as Gifted in State 2

	<i>N</i>	%	% FRL
No Gifted students	141	14%	53.72
< 2% Gifted FRL	429	44%	37.64
2-5% Gifted FRL	216	22%	51.09
5-7.5% Gifted FRL	63	6%	55.29
7.5-10% Gifted FRL	34	3%	56.50
> 10% Gifted FRL	92	9%	79.17

Table 8
Comparisons Among the Three Groups of Schools in State 2

Variable	Reference (<i>n</i> =573)		No Gifted (<i>n</i> =141)		No Gifted FRL (<i>n</i> =261)	
	Mean	<i>SD</i>	Mean	<i>SD</i>	Mean	<i>SD</i>
School % FRL	53.72	27.85	49.99	28.55	28.21	22.32
School % Gifted	5.33	7	0.96	1.06	3.97	3.91
District % FRL	47.94	19.56	44.67	19.45	31.94	16.07
District % Gifted	8.69	4.05	4.43	3.09	7.74	3.46
Prop Gifted FRL in cohort	0.05	0.06	0	0	0	0
READ	581.87	27.93	582.19	21.84	599.82	20.68
MATH	485.87	36.78	480.98	30.29	505.9	30.22
Reading Gap (by FRL)	31.04	27.03	25.73	24.96	31.31	23.96
Math Gap (by FRL)	40.05	32.57	32.18	29.03	43.74	31.35

Table 9

Frequencies of Students by Free and Reduced-price Lunch and Gifted Status in State 3

Gifted Status	FRL Eligibility		Total
	Not FRL	FRL	
Not Gifted	45,287	105,483	150,770
Gifted	10,184	7,490	17,674
Total	55,471	112,973	168,444

Table 10
Comparisons Among the Three Groups of Schools in State 3

Variable	Reference (<i>n</i> =1495)		No Gifted (<i>n</i> =343)		No Gifted FRL (<i>n</i> =201)	
	Mean	<i>SD</i>	Mean	<i>SD</i>	Mean	<i>SD</i>
School % FRL	70.0	24.0	83.0	18.0	54.0	25.0
School % Gifted	12.0	11.0	0.0	0.0	7.0	8.0
Prop Gifted FRL in cohort	0.12	0.11	0	0	0.07	0.08
READ 3rd grade	212.83	7.92	206.42	8.18	215.35	7.77
MATH 3rd grade	216.14	8.19	210.29	989	218.29	8.04
Reading Gap (by FRL)	10.9	8.29	9.89	9.92	11.56	7.57
Math Gap (by FRL)	10.64	8.31	9.11	10.05	11.33	8.18

Table 11

Breakdown of Schools by Percentage of Students by Free and Reduced-price Lunch Status and Identified as Gifted in State 3

	<i>n</i>	%	% FRL
No Gifted students	343	16.76	82.87
< 2% Gifted FRL	357	17.45	66.03
2-5% Gifted FRL	413	20.19	72.83
5-7.5% Gifted FRL	285	13.93	71.51
7.5-10% Gifted FRL	207	10.12	67.21
> 10% Gifted FRL	441	21.55	62.98

Table 12
Results of 3-level Multilevel Model–State 1

	<i>b</i>	<i>se</i>	<i>z</i>	95% CI	
GIFT5					
Reading	0.182	0.003	67.518	0.177	0.188
Math	0.244	0.003	86.353	0.239	0.250
FRL Status	-0.612	0.038	-16.031	-0.687	-0.537
School % GT	0.103	0.002	46.498	0.099	0.108
School % FRL	0.004	0.001	2.873	0.001	0.007
School Reading	-0.117	0.013	-8.671	-0.143	-0.090
School Math	-0.206	0.010	-20.562	-0.226	-0.186
District Math	0.015	0.031	0.492	-0.046	0.077
District Reading	-0.041	0.035	-1.168	-0.111	0.028
District % FRL	0.008	0.004	2.082	0.000	0.015
District % GT	0.021	0.005	4.040	0.011	0.031
Intercept	-3.490	0.039	-89.736	-3.566	-3.414
Variance Components					
Level 2					
Tau ₀₀ (School)	0.0014	0.0047			
Tau ₁₁ (School)	0.0121	0.0344			
Tau ₀₁ (School)	-0.004	0.0123			
Level 3					
Tau ₀₀	0.0136	0.0196			
Tau ₁₁ (District)	0.0454	0.0125			
Tau ₀₁ (District)	0.0049	0.0166			
AIC	39339.59				
BIC	39509.72				
loglikelihood	19651.80				
N	94069	1322	116		

Table 13
Results of 3-level Multilevel Model–State 2

	<i>b</i>	se	<i>z</i>	95% CI	
GIFT5					
Reading	0.018	0.000	38.646	0.017	0.019
Math	0.020	0.000	54.884	0.019	0.021
FRL Status	-0.302	0.074	-4.062	-0.447	-0.156
School % GT	0.109	0.003	40.157	0.104	0.114
School % FRL	0.002	0.002	1.062	-0.002	0.005
School Reading	-0.010	0.002	-4.494	-0.014	-0.006
School Math	-0.020	0.002	-12.8792	-0.023	-0.017
District Math	-0.003	0.004	-0.623	-0.011	0.006
District Reading	-0.003	0.006	-0.561	-0.014	0.008
District % FRL	-0.008	0.004	-2.193	0.016	-0.001
District % GT	0.082	0.013	6.329	0.057	0.108
Intercept	-4.114	0.060	-68.135	-4.232	-3.996
Variance Components					
Level 2					
Tau ₀₀ (School)	0.039	0.019			
Tau ₁₁ (School)	0.017	0.021			
Tau ₀₁ (School)	-0.025	0.02			
Level 3					
Tau ₀₀ (District)	0.133	0.036			
Tau ₁₁ (District)	0.20	0.043			
Tau ₀₁ (District)	-0.035	0.028			
AIC	39339.59				
BIC	39509.72				
loglikelihood	19651.80				
N	57811	1032	179		

Table 14
Results of 3-level Multilevel Model–State 3

	<i>b</i>	<i>se</i>	<i>z</i>	95% CI	
GIFT5					
Reading	0.058	0.001	78.777	0.056	0.059
Math	0.052	0.001	74.496	0.050	0.053
FRL	-0.244	0.054	-4.545	-0.349	-0.139
District % FRL	0.201	0.382	0.526	-0.548	0.949
School % FRL	-0.158	0.101	-1.567	-0.357	0.040
School % GT	10.608	0.158	66.953	10.297	10.918
District % GT	4.856	0.560	8.677	3.759	5.952
School Reading	-0.047	0.005	-9.785	-0.057	-0.038
School Math	-0.053	0.004	-14.213	-0.060	-0.046
District Math	0.0064	0.014	0.571	-0.019	0.034
District					
Reading	-0.0185	0.021	-0.276	-0.044	0.033
Intercept	-3.557	0.036	-97.097	-3.600	-3.457
Variance Components					
Level 2					
Tau ₀₀ (School)	0.051	0.011			
Tau ₁₁ (School)	0.185	0.030			
Tau ₀₁ (School)	-0.072	0.016			
Level 3					
Tau ₀₀ (District)	0.073	0.019			
Tau ₁₁ (District)	0.170	0.028			
Tau ₀₁ (District)	-0.024	0.019			
AIC	65547.32				
BIC	65727.94				
LogLik	-32755.66				
N	168444	2194			73

Table 15

School Level Correlations Among Reading, Percentage of Free and Reduced-price Lunch, and Percentage of Gifted Students in State 1

	Reading	Math	% FRL	% Gifted
Reading	1			
Math	0.89	1		
% FRL	-0.80	-0.73	1	
% Gifted	0.58	0.54	-0.64	1

Table 16

School Level Correlations Among Reading, Percentage of Free and Reduced-price Lunch, and Percentage of Gifted Students in State 2

	Reading	Math	% FRL	% Gifted
Reading	1.00			
Math	0.92	1.00		
% FRL	-0.82	-0.77	1.00	-
% Gifted	0.40	0.43	-0.31	1.00

Table 17
School Level Correlations among Reading, Percentage of Free and Reduced-price Lunch, and Percentage of Gifted Students in State 3

	Reading	Math	% FRL	% Gifted
Reading	1			
Math	0.74	1		
% FRL	-0.67	-0.47	1	
% Gifted	0.55	0.47	-0.56	1

Table 18
Results of 2-level Multilevel Model–State 1

	Model 1 coefficient (SE)	Model 2 coefficient (SE)	Model 3 coefficient (SE)
Model for school proportion of students identified as gifted (β_{0j})			
Intercept (γ_{00})	.16*** (.01)	.16*** (.01)	.16*** (.01)
District proportion of FRL eligible students (γ_{01})		-.22*** (.04)	-.07 (.07)
Mean district reading (γ_{02})			-.01 (.01)
Mean district math (γ_{03})			.02* (.01)
Model for school proportion of FRL eligible students slope (β_{1j})			
Intercept (γ_{10})		-.36*** (.02)	-.17*** (.01)
Model for mean school reading (β_{2j})			
Intercept (γ_{20})			.01*** (.00)
Model for mean school math (β_{3j})			
Intercept (γ_{30})			.01*** (.00)
Variance			
Level 1 (<i>within-districts</i>)			
Var(σ^2)	0.01	0.004	0.004
Level 2 (<i>between-districts</i>)			
Var (τ_{00})	0.003	0.003	0.003
Information criteria			
Deviance	-2183.39	-3150.64	-3352.25
Parameters	2	2	2
Number of schools		1316	
Number of districts		114	

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 19
Results of 2-level Multilevel Model–State 2

	Model 1 coefficient (SE)	Model 2 coefficient (SE)	Model 3 coefficient (SE)
Model for school proportion of students identified as gifted (β_{0j})			
Intercept (γ_{00})	.07*** (.01)	.06*** (.01)	.06*** (.01)
District proportion of FRL eligible students (γ_{01})		-.09** (.03)	-.08*** (.02)
Mean district reading (γ_{02})			-.00 (.00)
Mean district math (γ_{03})			.00 (.00)
Model for school proportion of FRL eligible students slope (β_{1j})			
Intercept (γ_{10})		-.19*** (.04)	-.04 (.03)
Model for mean school reading (β_{2j})			
Intercept (γ_{20})			.00 (.0)
Model for mean school math (β_{3j})			
Intercept (γ_{30})			.00*** (.00)
Variance			
Level 1 (<i>within-districts</i>)			
Var(σ^2)	0.01	0.007	0.007
Level 2 (<i>between-districts</i>)			
Var (τ_{00})	0.002	0.002	0.002
Information criteria			
Deviance	-1813.99	-2022.00	-2087.08
Parameters	2	2	2
Number of schools		1032	
Number of districts		181	

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

Table 20
Results of 2-level Multilevel Model–State 3

	Model 1 coefficient (SE)	Model 2 coefficient (SE)	Model 3 coefficient (SE)
Model for school proportion of students identified as gifted (β_{0j})			
Intercept (γ_{00})	.07*** (.01)	.06*** (.00)	.06*** (.00)
District proportion of FRL eligible students (γ_{01})		-.11** (.03)	-.09 (.05)
Mean district reading (γ_{02})			.00 (.00)
Mean district math (γ_{03})			.00 (.00)
Model for school proportion of FRL eligible students slope (β_{1j})			
Intercept (γ_{10})		-.16*** (.01)	-.03** (.01)
Model for mean school reading (β_{2j})			
Intercept (γ_{20})			.00*** (.00)
Model for mean school math (β_{3j})			
Intercept (γ_{30})			.00*** (.00)
Variance			
Level 1 (<i>within-districts</i>)			
Var(σ^2)	0.01	0.008	0.007
Level 2 (<i>between-districts</i>)			
Var (τ_{00})	0.001	0.001	0.001
Information criteria			
Deviance	-3847.22	-4219.94	-4502.02
Parameters	2	2	2
Number of schools		2194	
Number of districts		73	

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

Level 1: (i Students)

$\text{Log}(\text{Odds gifted}_{ijk} = 1 \text{ vs. } 0)$

$$\begin{aligned} &= \pi_{0jk} + \pi_{1jk}(\text{ever_frl}_{ijk}) + \pi_{2jk}(\text{read}_{ijk} - \overline{\text{read}}) \\ &+ \pi_{3jk}(\text{math}_{ijk} - \overline{\text{math}}) \end{aligned}$$

Level 2: (j schools)

$$\begin{aligned} \pi_{0jk} &= \beta_{00k} + \beta_{01k}(s_frl_{jk} - \overline{s_frl}) + \beta_{02k}(s_gifted_{jk} - \overline{s_gifted}) \\ &+ \beta_{03k}(s_read_{jk} - \overline{s_read}) + \beta_{04k}(s_math_{jk} - \overline{s_math}) \end{aligned}$$

$$\pi_{1jk} = \beta_{10k} + r_{jk}$$

$$\pi_{2jk} = \beta_{20k}$$

$$\pi_{3jk} = \beta_{30k}$$

$$\pi_{4jk} = \beta_{40k}$$

Level 3: (k districts)

$$\begin{aligned} \beta_{00k} &= \gamma_{000} + \gamma_{001}(d_frl_k - \overline{d_frl}) + \gamma_{002}(d_math_k - \overline{d_math}) \\ &+ \gamma_{003}(d_reading_k - \overline{d_reading}) + \gamma_{004}(d_gift_k - \overline{d_gift}) + u_{00k} \end{aligned}$$

$$\beta_{01k} = \gamma_{010}$$

$$\beta_{02k} = \gamma_{020}$$

$$\beta_{03k} = \gamma_{030}$$

$$\beta_{04k} = \gamma_{040}$$

$$\beta_{10k} = \gamma_{100} + u_k$$

$$\beta_{20k} = \gamma_{200}$$

$$\beta_{30k} = \gamma_{300}$$

$$\beta_{40k} = \gamma_{400}$$

Figure 1. Equation for the full three-level models.

Level: 1 (i Schools)

$$s_gifted_{ij} = \beta_{0j} + \beta_{1j}(s_frl_{ij} - \overline{s_frl}_j) + \beta_{2j}(s_read_{ij} - \overline{s_read}_j) \\ + \beta_{3j}(s_read_{ij} - \overline{s_read}_j) + r_{ij}$$

Level: 2 (j districts)

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(d_frl_j - \overline{d_frl}) + \gamma_{02}(d_math_j - \overline{d_math}) \\ + \gamma_{03}(d_read_j - \overline{d_read})$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

Figure 2. Equation for full two-level models.

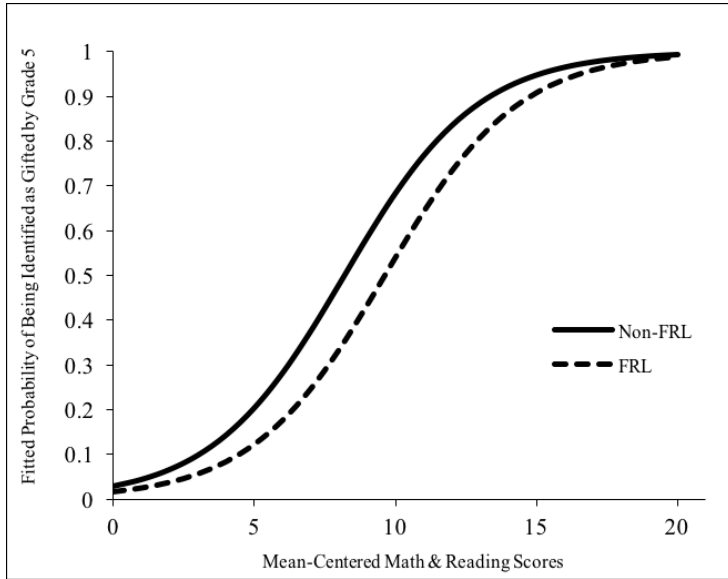


Figure 3. FRL and non-FRL probability of identification–State 1.

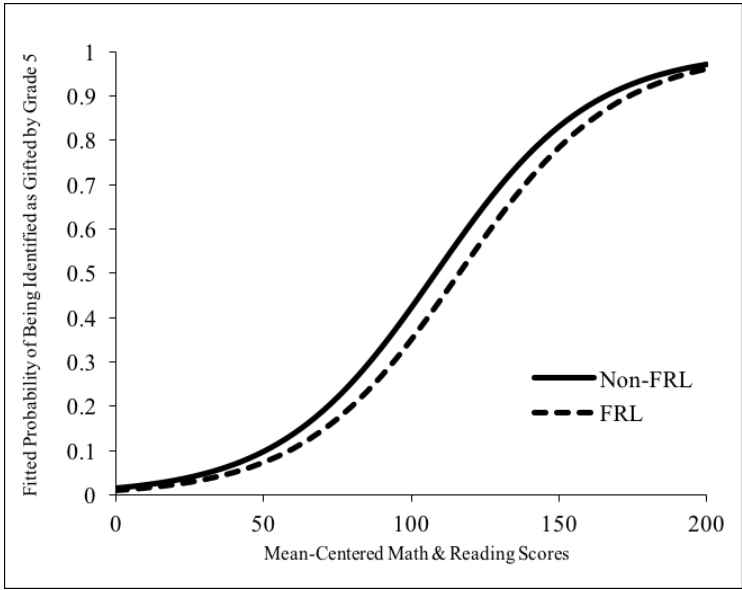


Figure 4. FRL and non-FRL probability of identification–State 2.

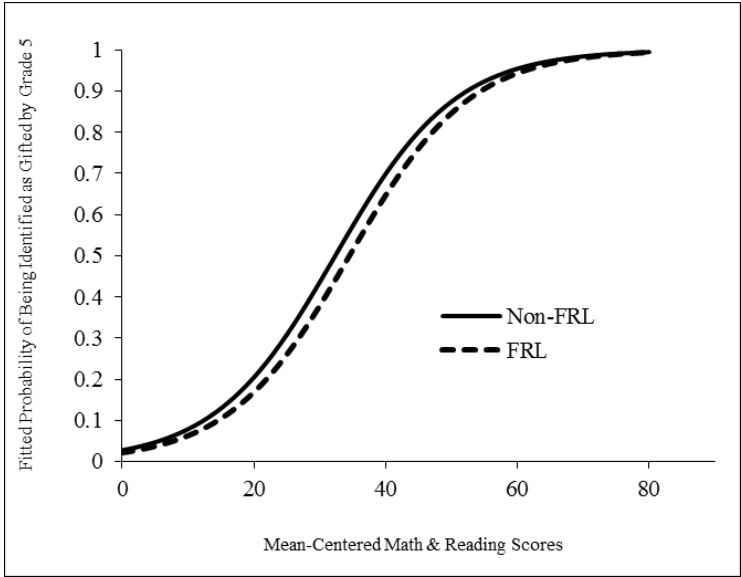


Figure 5. FRL and non-FRL probability of identification–State 3.