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The Potential Promises and Pitfalls of Using Local Norms for Gifted Identification

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ABSTRACT

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M. Sabrina Hartman

Who are the gifted? This question has plagued the field since its inception. Historically, gifted education has been predicated on the values of the Caucasian, upper- to middle-class majority. As a result, underrepresentation of students from economically disadvantaged and culturally diverse families have been well documented in the literature and continues to this day. Some scholars have suggested the use of expanded definitions of giftedness to increase participation of students from underrepresented segments of the population. This study used regression and hierarchical linear models to predict the proportion of students identified across various thresholds focusing on how definitions impacted differential rates of gifted identification across schools with different proportions of students who are eligible for free and reduced lunches (FRL) and school locale. Results indicated that when school building norming procedures were used with cut scores associated with the top 5%, 10%, or 20% of students that school proportion of FRL students was either unrelated or positively related to proportion of identified students. Local school-based norming also led to more equal distributions of identified gifted students across schools serving diverse populations.

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Statement of the Problem

High-poverty schools are characterized by less prepared teachers, lower teacher expectations, low levels of parent involvement, and academic declines during the summer months (Entwisle & Alexander, 1999; Murnane, 2007; Olszewski-Kubilius & Clarenbach, 2012; Olszewski-Kubilius & Thomson, 2010; Subotnik, Olszewski-Kubilius, & Worrell, 2011). Consistent findings in the literature also indicate that students who qualify for subsidized lunches are underrepresented in gifted programs relative to their proportion in the school-aged population (Donovan & Cross, 2002; Ford, 1998; Harris & Ford, 1999; McBee, 2006; Olszewski-Kubilius & Clarenbach, 2012; Wyner, Bridgeland, & Diiulio, 2007). This gap between low socioeconomic status (SES) students and higher SES students at the highest levels of achievement is called the income excellence gap which results in low income students being much less likely to be identified for gifted services (Hardesty, McWilliams, & Plucker, 2014; McBee, 2010) .

It is paradoxical that high-poverty schools are just as likely as low-poverty schools to have gifted programs and yet students at low-poverty schools are twice as likely to receive gifted services than students at high-poverty schools (Yalma & Tyner, 2018). Put more simply, this means that gifted programs at high-poverty schools serve far fewer students. This could be due to the use of strict cut off scores in combination with unfair norming procedures which do not take student context into account. A few scholars have suggested the use of school-based norming procedures as a method to introduce more economically disadvantaged students to appropriately challenging curricula and help prepare them for rigorous secondary coursework (Lohman, 2005; Olszewski-Kubilius & Corwith, 2018; Peters & Engerrand, 2016; Peters & Gentry, 2012; Plucker & Peters, 2018). As will be discussed in the following section, not only do student level variables negatively impact academic achievement for children living in poverty, but school and neighborhood variables can also promote low level of academic achievement. While the inequalities in the rates of gifted identification and school proportion of FRL students has been thoroughly studied the relationship between school location and gifted identification has not been sufficiently examined (McBee, 2010; Olszewski-Kubilius & Corwith, 2018; Peters & Engerrand, 2016; Plucker & Peters, 2018). In this study I used school locale (i.e. urban, suburban, rural) as a proxy for school location and investigated the impact of school locale on proportion of identified gifted students after controlling for proportion of students receiving subsidized lunches. I also explored some potential drawbacks of school-based norming procedures as a method of gifted identification. The purpose of this research was to determine whether school building norming procedures would result in a more equal distribution of proportion of identified students across schools in a single state. Since poverty is a social construct its effect on child development and educational outcomes is complex and multifaceted. Despite this, a review of the literature on how poverty influences academic achievement and gifted education as it relates to this study follows.

Review of Literature

How poverty affects academic achievement

The negative effects of economic disadvantage on child development have been well established in the literature (Barton, 2009; Engle & Black, 2008; Entwisle & Alexander, 1999; Reardon, 2011; Reardon & Portilla, 2016; Rutkowski, Rutkowski, & Plucker, 2012; Subotnik et al., 2011). A more recent finding has included the link between duration of time spent in poverty and academic achievement (Michelmore and Dynarski, 2016; National Institute of Child Health and Human Development Early Child Care Research Network, 2005). In one study, the sample (n = 1,364) was recruited throughout the United States, and then separated into four income classifications: families with incomes never below the poverty line, families with children disadvantaged from birth to three years of age but not afterwards, families with children disadvantaged between four to nine years of age, and families with incomes below the poverty line for the entirety of the study (National Institute of Child Health and Human Development Early Child Care Research Network, 2005). Baseline hierarchical linear models revealed statistically significant group differences in cognitive development with those children who had never been disadvantaged scoring the highest, children who were persistently disadvantaged scoring lowest, and children in the early disadvantaged and late disadvantaged groups scoring between the two other groups. Home access to learning materials and maternal sensitivity were found to be statistically significant mediators ($p < .001$).

Economic disadvantage is associated with fewer intellectual resources and opportunities in the home and at school (Berliner, 2009; Olszewski-Kubilius & Thomson, 2010; Robinson & Clinkenbeard, 1998). Differential access to educational opportunities, including gifted education, compounds over time which results in the finding that the income achievement gap, the difference in achievement scores between economically disadvantaged and more advantaged children at levels of minimal proficiency, increases as students advance through the educational system and impacts post-secondary enrollment (Hardesty et al., 2014; Olszewski-Kubilius & Thomson, 2010; Plucker, Burroughs, & Song, 2010; Reardon, 2011; Reardon & Portilla, 2016). This trend was a finding in a study of longitudinal data from the Michigan public school students (Michelmore and Dynarski, 2016). Nearly 60% of Michigan students were eligible for free or reduced priced lunches (FRL) at least one year from kindergarten to Grade 8 and 14% were eligible all nine years. Children who were FRL eligible all nine years between kindergarten and Grade 8 scored, on average, 0.94 standard deviations below children who had never been eligible. The first year students became eligible their Grade 8 mathematics score (the dependent variable) decreased an average of 0.33 of a standard deviation, for each additional year their mathematics score decreased by 0.08 of a standard deviation.

This linear trend suggests that students who are persistently disadvantaged face more impediments to high academic achievement than students who are intermittently disadvantaged. Thus, a dichotomous variable representing a student's current FRL status may not be enough to account for differences in opportunities to learn (Michelmore and Dynarski, 2016; National Institute of Child Health and Human Development Early Child Care Research Network, 2005). Since SES gaps within a single school are approximately half as large as the distribution of the national population of students in a single grade, local school-based norming procedures may better account for student context than state or district norming procedures (Duncan & Magnuson, 2005).

While the relationship between parental education and academic achievement has remained stable over the past fifty years; the predictive power of family income has sharply increased (Reardon, 2011). An analysis of 19 nationally representative studies concluded that the income achievement gap has been steadily increasing since the mid-1970s between the richest students and the poorest students. For the cohort born in 2000, the income achievement gap was 1.25 standard deviations, an increase of about 30% from the cohort born in 1970. For students born between the mid-1990s and early 2000s, upon kindergarten entry the income achievement gap was about twice as large as the African American-Caucasian achievement gap.

One student level variable that has been shown to affect academic achievement over and above family characteristics is neighborhood a child lives in (Berliner, 2009; Leventhal & Brooks-Gunn, 2000; Nelson & Sheridan, 2011; Reardon, 2011; Wyner et al., 2007). Children who grow up in the wealthiest neighborhoods are up to three times more likely to graduate from high school and college than children who grow up in the poorest neighborhoods (Nelson & Sheridan, 2011; Owens, 2010; Wyner et al., 2007). This was evidenced in Owen's (2010) study of survey data between 1990 and 2010 which analyzed data from secondary school students (n = 11,097). Multilevel logit models were used to determine the likelihood of obtaining a high school diploma or a bachelor's degree. Analyses revealed that for high school graduation, school characteristics accounted for 3.5% of the variance in educational outcomes and neighborhood characteristics explained an additional 2.5%. For college graduation, school characteristics explained 12% of the variance and neighborhoods explained an additional 4%. Students who lived in neighborhoods with higher occupational attainment and had parents with high educational attainment were statistically significantly more likely to graduate both high school and college. The neighborhoods students live in explained a portion of variability in educational attainment even after controlling for student-level variables (i.e. home enrichment, family income, parental involvement, etc.) and school-level variables (i.e. proportion of teaching staff with advanced degrees, behavioral disturbances, etc.). In this study school locale is used as a proxy for student neighborhood to observe how much unique variance can be explained after controlling for proportion of FRL students.

Suppose there are two hypothetical children, one child has college educated parents with professional careers and one has high school educated parents who often experience job instability. The literature predicts there will be a gap between these children's academic achievement test scores as early as kindergarten entry (Engle & Black, 2008; Hardesty et al., 2014; Michelmore & Dynarski, 2016; National Institute of Child Health and Human Development Early Child Care Research Network, 2005; Oakes, Ormseth, Bell, & Camp, 1990). What is surprising, and contrary to the American value of social equality, is that schools do little to decrease the gap between low SES and high SES students over the course of primary and secondary education. This could be partially due to the differential rates of gifted identification between low-poverty schools and high-poverty schools.

Current practices of schooling reserve development of academic performance at the highest levels of achievement for those students nested within schools and families with more financial resources (Entwisle & Alexander, 1999; Olszewski-Kubilius & Corwith, 2018; Reardon, 2011). Student level variables place children on various long-term achievement trajectories, which later translate into differential educational attainment and income (Chetty, Friedman, and Rockoff, 2011; Duncan & Magnuson, 2011; Entwisle & Alexander, 1999; Owens, 2010; Yalma & Tyner, 2018). The large and growing number of students who qualify for FRL and the correlation between poverty and decreased academic success, leads some scholars to worry about the future of the nation's workforce, especially in an economy that increasingly rewards highly-educated employees (Olszewski-Kubilius & Clarenbach, 2012; Olszewski-Kubilius & Corwith, 2018; Rutkowski, Rutkowski, & Plucker, 2012).

Gifted Education

It is well established in the literature that students receiving free or reduced priced lunches are underrepresented in gifted education programs relative to their proportion in the population, further indicating current inequities of educational opportunities (J. Borland, 2004; Hamilton et al., 2017; Olszewski-Kubilius & Thomson, 2010). There is some debate over what methods could be used to increase identification of FRL students because they typically underperform on the standardized achievement tests used to make identification decisions (National Association for Gifted Children, 2015; Michelmore and Dynarski, 2016; Olszewski-

Kubilius & Thomson, 2010, Reardon, 2011). A few scholars have suggested the use of school-based local norms as a possible way to reduce the underrepresentation problem (McBee, 2010; Olszewski-Kubilius & Corwith, 2018; Peters & Engerrand, 2016; Plucker & Peters, 2018). Using district-wide norming procedures among schools with different levels of achievement could lead to very few students being identified in schools with the highest proportion of students receiving FRL within districts (Hamilton et al., 2017). However, even within the poorest schools there are a group of students who are academically more advanced than their peers and thus require additional services outside the general classroom to be challenged by the curriculum (Ford, 2003; Peters, Rambo-Hernandez, Makel, Matthews, & Plucker, 2017; Reis & Renzulli, 2010)

Improved methods for identifying students from low-income backgrounds for gifted education services could help provide a more responsive education to economically disadvantaged students (Lohman, 2005; Olszewski-Kubilius & Corwith, 2018; Peters & Engerrand, 2016; Peters & Gentry, 2012; Plucker & Peters, 2018). One popular method of identification and gifted programing that has been studied in a range of school serving different SES populations is Renzulli's (1978) Revolving Door Identification and Programming (RDIM) model of providing gifted services. This model aims to provide a of continuum of services that can be modified based on individual student's interests and needs, services may include differentiation in the regular classroom, guidance for production of creative products in a resource room, or other program activities (Callahan & Miller, 2005; Renzulli, 1988). The purpose of this program is to find students who are not appropriately challenged by their current curricula and provide time for them to investigate academic areas of their own choosing. Curriculum compacting allows students to test out of material they have already mastered and "buy" time for such enrichment activities.

Many states leave the regulations for identification practices and delivery models for gifted services up to the preferences of individual districts (Brown, Avery, VanTassel-Baska, Worley, & Stambaugh, 2006; Subotnik et al., 2011). The fragmentation of policies at the state, district, and locale levels makes the task of speaking about the field of gifted education in the country difficult (Brown et al., 2006; National Association for Gifted Children, 2015). A study of five state's gifted policies reported how varied gifted programming can, be both between and within states (Brown et al., 2006). Lack of accountability procedures were the biggest problem across the states. The absence of on-site evaluation for gifted programs meant that there was a dearth of information regarding whether the policies outlined in the governing documents were being effectively carried out at the school level (Brown et al., 2006). Out of all the state and local documents, identification processes were discussed the most; though only two states tracked numbers of identified gifted students by demographics.

Various studies suggest that as a nation we reserve the cultivation of academic talent at the highest levels of achievement to those students nested within schools or families who possess greater economic resources (McBee, 2010; Plucker et al., 2010; Subotnik et al., 2011). The inadequate educational opportunities many high-ability students receive in high-poverty schools is a social inequity that has consequences, such as strengthening social divides, promoting cycles of intergenerational poverty, and severely limiting social mobility (Yalma & Tyner, 2018). Students make the largest achievement gains in early elementary school, so it follows that a student's time in elementary school is influential in determining his or her eventual educational attainment (Entwisle & Alexander, 1999; Reardon, 2011; Zigler, Gilliam, & Jones, 2006). Learning does not occur devoid of context or student inputs (e.g. school readiness, SES, parental involvement in schooling) which impact educational outcomes. The purpose of this study is to examine whether implementation of school norming procedures could reduce the effect of socioeconomic status on access to necessary educational opportunities outside the general education classroom (Olszewski-Kubilius & Clarenbach, 2012).

The Current Study

The 20% highest achieving students at a low-poverty schools will likely score very differently from the 20% highest achieving students at high-poverty schools but both will likely require additional educational opportunities outside the general classroom to prevent their academic achievement from plateauing (Callahan & Miller, 2005; Reis & Renzulli, 2010; Subotnik et al., 2011). As communities and schools become more economically segregated and larger proportions of students fall below the poverty line, steps need to be taken to help bolster disadvantaged students' probability of success (Owens, 2010; Owens, Reardon, & Jencks, 2016; Plucker & Peters, 2018). There have been many studies quantifying the unequal educational opportunities for children of different social classes and exploring how income gaps develop over time but few scholars that have put forth school-based local norms as a possible solution (McBee, 2010; Olszewski-Kubilius & Corwith, 2018; Peters & Engerrand, 2016; Plucker & Peters, 2018).

As a result of the increasing social stratification of neighborhoods and the relatively small size of elementary schools, school quality (e.g. quality and number of teachers, curriculum) varies largely as a function of the financial resources of one's neighborhood, and students in the same school tend to have similar SES backgrounds (Entwisle & Alexander, 1999; Owens, 2010; Owens et al., 2016; Plucker & Peters, 2018). Using school locale as a proxy for neighborhood, the models in this study aim to examine the variability in proportion of identified gifted students between schools by altering the cut score using several norming procedures. Applying local norming procedures may more accurately reflect the educational opportunities and resources children have received in the past. A possible benefit of using local norms could be a decrease in the correlation between school variables (i.e. proportion of students eligible for FRL, locale code) and proportion of students identified as gifted. However, there are also some potential disadvantages of utilizing school-based norms: extreme variability in cut scores, particularly within districts, and the possibility of students being identified for gifted services with scores below state proficiency level. If a student was identified for gifted services while scoring below proficiency level, he or she may be unprepared for the next testing period if gifted services are not related to topics on state assessments. Students scoring below proficiency level has consequences in today's accountability-focused school environments (Barton, 2009). The purpose of this study is to explore these possibilities.

Methods

Research questions

The research questions for this study are: (1) when state norming procedures are implemented how much variability can be accounted for using school locale and proportion of students who receive subsidized lunch as predictors?; (2) when district norming procedures are implemented how much variability can be accounted for using school locale and proportion of students who receive free or reduced lunch as predictors?; (3) when school norming procedures are implemented how much variability can be accounted for using school locale and proportion of students who receive free or reduced lunch as predictors?; (4) when school norming procedures are implemented, what proportion of students would qualify for gifted services with scores below state proficiency level?; and (5) when school norming procedures are applied, how much variability in cut score exists within and between districts and how much of the variability can be explained with the addition of the FRL predictors? Spring 2017 data was selected because it was the most recent data available, and the test in the sample state, the Measure of Academic Progress (MAP), was taken around the same time as the Partnership for Assessment of Readiness for College and Careers (PARCC) in other states. The PARCC tests are summative assessments that can be statistically linked to MAP scores. MAP scores are vertically scaled across grades K-12 and are reported using the Rasch Unit (RIT) scale which ranges from 100 to 300 (Northwest Evaluation Association, 2016). The vertical scaling allows the scores of students K-12 to be reported on the same metric and implies that scores across the scale are equidistant from each other (Iowa Testing Programs, n.d.).

Three cut score percentages were selected for this study 5%, 10% and 20%. The gifted child paradigm was the preeminent paradigm of providing gifted services for the majority of the 20^{th} century and defined gifted students as those who score in the top 3% to 5% of the general population on intelligence tests (Dai & Chen, 2013; Delisle, Reis, & Gubbins, 1981). On the other hand, Renzulli's (1982) Revolving Door Identification and Programming model suggested providing a continuum of services to the top 15% to 20% in each school. While the 10% threshold was included as an intermediate option between these two extremes.

Based on the literature, I expect suburban schools to have the highest proportion of identified students across all norming procedures and thresholds due to the lower concentration of poverty and the higher concentration of highly-educated parents (Duncan & Magnuson, 2005; Leventhal & Brooks-Gunn, 2000; Michelmore & Dynarski, 2016). I also expect the slope of the FRL variable to be less negative when applying district norms when compared to state norms and the FRL slope to be statistically nonsignificant when school norming procedures are in place (Hamilton et al., 2017; Lohman, 2005; Reis & Renzulli, 1982).

Sample and Measures

Data consisted of Grade 3 student scores on the Measure of Academic Progress (MAP) standardized tests in mathematics (*n* = 93,550) and reading (*n* = 93,057) during Spring 2017 (Northwest Evaluation Association, 2016). The computer adaptive nature of the MAP assessments mean that students can be tested on items that are at, below, or above the students' grade level depending on responses to previous items, which help to eliminate ceiling and floor effects (Northwest Evaluation Association, 2013). The field testing and vertical scaling of the assessments make them reliable measures of academic growth which have been administered to over 8 million K-12 students. The sample of scores come from Grade 3 students from a populous midwestern state with a range of school settings. (e.g. urban, suburban, town, rural). There were 251 students who had multiple observations between the reading and mathematics data sets; in these cases, I kept the most recent score. Multiple observations could be due to a student moving to a different school or repeating a grade. After deleting 746 cases because they belonged to students at schools with fewer than 10 students, the data set for mathematics consisted of 1431 schools nested within 458 districts. The reading data set consisted of 1333 schools nested within 458 districts. Schools ranged from 10-334 student scores per subject. In the reading data set, 126 schools did not have a value for proportion of students receiving FRL and 28 schools did not have data for urban locale. In the math data set, 123 schools had no information for FRL and 27 lacked an urban locale code.

Variables.

For the first research question, gifted referred to students who had MAP scores associated with the top 5%, 10%, and 20% in the state. The 5% threshold was chosen because state norming often yields similar identification patterns as national norming and was selected to investigate what occurs when such a competitive standard for gifted services is implemented (Peters et al., In Press). It is possible using this definition that the schools with high proportions of identified students will be homogenous in terms of the FRL variable or urban locale.

For the second research question, gifted referred to students who obtained MAP scores that are in the top 5%, 10%, and 20% in their district and the third, fourth, and fifth research questions referred to the top 5%, 10%, and 20% of performers in each school. For all the research questions, the proportion of students eligible for free or reduced priced lunches (FRL) variable was entered as a percentage of students receiving FRL and was centered around the grand mean. The school locale code was dummy coded with the first contrast variable comparing urban schools to suburban schools, the second contrast comparing suburban schools to rural schools, and the third dummy comparing suburban to town schools.

Data Analyses

Research question 1. The first research question defined giftedness as the top 5%, 10%, and 20% of students in the state. I calculated the cut score associated with the top 5% of students, by multiplying the z score of 1.65, the point which has 95% of the normal distribution to the left, by the standard deviation of the RIT scores in either reading or math and then adding this product to the state mean for mathematics (M = 202.81) and reading (M = 210.71). The cut score associated with the top 10% of students was calculated by following the same procedure but multiplying by a z score of 1.29, and a z score of 0.85 for the top 20%. First, I ran a regression of a model with only the FRL predictor estimating the proportion of students identified as gifted in each school. In the first model, $y_i = \beta_0 + \beta_1(\%FRL) + \varepsilon_i$, β_0 estimated the average proportion of gifted students at a school with the average proportion of FRL students and β1 represented the expected change in proportion of gifted students per increase of 1 percentage point on the FRL metric.

Next, I added in school locale using three dummy codes as predictors along with interaction effects, which were the products of the grand mean centered FRL predictor and each dummy coded contrast. The interaction effects allowed the slope for FRL to vary for each type of school locale. The second model was Y_i=β_0(intercept)+β_1(%FRLforsuburban)+β_2(urban)+β_3(town)+β_4(rural)+ β_5(urbaninteraction)+ β_6(towninteraction)+ β_7(ruralinteraction)+ ε_i. β_0 represented the mean proportion of identified gifted students in suburban schools at the mean FRL. β_1 was the rate of change for suburban schools not at the mean FRL. β_2 was the differential for the intercept for urban schools holding FRL constant at the mean. β_3 the differential for the intercept for town schools holding FRL constant at the mean, and β_4 was the differential for the intercept for rural schools, holding FRL constant at the mean. β_5 was the differential slope for FRL for urban schools. When β_5 was statistically significant it meant that for urban schools the effect of FRL on the proportion of identified gifted students was statistically significantly different from suburban schools. β_6 represented the FRL slope differential for town schools and β_7 represented the FRL slope differential for rural schools.

These results were used to calculate how much more variance (R^2) was explained in the second model than the first model. Then, I used the coefficients from the second model to estimate predicted values for each of the four locales using three FRL percentages: one at the mean proportion FRL across schools, one at one standard deviation above the mean, and one at one standard deviation below the mean.

Research question 2. In the mathematics data set, 285 schools were deleted, because each district was composed only of a single school thus would reflect school-based norming rather than district wide norming; this analysis was run on a sample of 1145 schools nested within 136 districts. In the reading dataset, 284 schools were deleted, and the analysis included the remaining 1148 schools nested within 137 districts. Using a similar procedure for calculating cut scores as research question one, I multiplied each z score by the standard deviation in each district and added this product to the mean for each district. Using the same procedure as in research question one, I ran a model with only FRL as a predictor and then added in the dummy codes and interactions as a set. I then observed how R^2 changed between the model with only FRL as a predictor and the model which included dummy codes and interaction terms.

Research question 3. To calculate the cut score associated with the top performers in each school I used the same procedure as research questions one and two; unlike the second research question, I utilized the entire sample of schools of 1333 for reading and 1431 for mathematics. The first model used only FRL as a predictor and the second model added in the dummy codes and interaction effects. I observed how R^2 changed between the baseline model and the more complex model.

Research question 4. Since the state in the study only utilized MAP test scores, in order determine benchmark standards, such as minimum proficiency, they had to be converted to Partnership for Assessment of Readiness for College and Careers (PARCC) scores. By matching scores from PARCC participating states, researchers were able to use a student's percentile rank to predict future performance on PARCC exams from interim MAP scores. MAP reading scores correctly predicted proficiency status on PARCC English language arts test 83% of the time and at a rate of 88% for the mathematics assessments. Student MAP scores had to be translated into approximate PARCC scores and then compared to benchmark standards. The PARCC assessments have four performance levels: Level 1: did not yet meet expectations; Level 2: partially met expectations; Level 3: approached expectations; Level 4: met expectations (proficiency level); and Level 5: exceeded expectations.

SPSS identified students who were among the top performers in a school using local norms and had scores below proficiency level for spring 2017 (Northwest Evaluation Association, 2016). The minimum proficiency cut score for Grade 3, was 208 for the mathematics test and 205 on the reading exam. I then counted the number of students who qualify for gifted services with scores below proficiency level. I carried out this procedure three time for the three percentage cut scores in each subject.

Research question 5. The purpose of this research question was to measure how large the range of cut scores were at each threshold within and between districts when school-based norming was applied and to consider the nesting of schools into districts. Districts contained between 2 to 405 schools with a mean of 8.42 schools per district. Since the coefficients for the 10% school norming threshold in reading and math were all an intermediate between the values of the 5% and 20%, I decided to only include the 5% and 20% thresholds for this analysis. I located the scores associated with the top 5% and 20% in each school using the same identification procedure as research question three. The two cut scores in each subject served as the dependent variable in hierarchical linear modeling (HLM) models. The first model contained no predictors, which allowed me to calculate the intraclass correlation (ICC), a ratio that describes the variance that lies between level-two units (districts) compared to the variance between level-one units (schools). The notation for level-two variance is τ_{00} and the notation for level-one variance is σ^2, so the ICC was calculated using the formula $\tau_{00}/ (\tau_{00} + \sigma^2)$. Upon adding the grand mean-centered FRL variable, I calculated how much within district variability was reduced with the addition of the FRL predictor using the formula $[\sigma^2_{baseline} - \sigma^2_{fitted}]/\sigma^2_{baseline}$.

Results

In the mathematics data set, 614 schools were in an urban locale, 531 schools were in a suburban locale, 57 schools were in a town locale, 88 schools were in a rural locale, and 27 schools had this variable missing. Across the four locales, 105 schools were missing the FRL variable. More descriptive statistics for this data set can be found in Table 1. In the reading data set urban schools had a mean proportion of FRL students of 80.52%, suburban schools had a mean of 47.31%, town schools had a mean FRL of 58.97%, and rural schools in the sample had a mean of 41.76%. More descriptive statistics for this data set can be found in Table 2. Across the four locales, 190 schools were missing the FRL variable. As can be seen in Table 1 and Table 2 proportion of FRL students partially overlaps with school locale. Urban and town schools had a higher proportion of FRL students while suburban and rural schools had lower proportions of FRL students. However, there were schools within each locale grouping that ranged from 20% FRL to 99% FRL indicating that school locale would be able to explain additional variance after controlling for the FRL predictor.

In the data sets for both subjects the correlation between proportion of FRL students and identified students was strongest when using a 20% statewide cut score. The correlation decreased markedly upon using district norms and decreased further upon implementation of school-based norming. Correlations for each regression model for mathematics are in Table 3. In both the reading and mathematics data sets the FRL slope was statistically nonsignificant at the 5% threshold and positive and statistically significant at the 20% threshold, as can be seen in Table 4.

A positive correlation indicates that based on the regression model more FRL students predicted more identified gifted students. This was strange because I set every school to identify the same proportion of their student body so there should not be any statistically significant correlation.

Research question 1. The first research question examined how much variability could be explained when implementing state norming procedures. For the mathematics data set using a 5% state cut score, in the first step of the analysis about 17% of the variance of proportion of identified students at each school was explained. Upon adding dummy codes and interaction effects for school locale, 10.8% more variance was able to be explained. The second step of the model predicted that for a suburban school with the mean proportion of FRL, 2.4% would be identified as gifted. For every additional 10% of the student population that is FRL eligible the model predicted that 1.2% fewer students would be considered gifted using this threshold. This model predicted no virtually no students would be identified at a school with 100% of the students receiving free lunch.

At the 10% threshold the first model explained 29.5% of the variance and the second model explained 40.7% of the variance. At the 20% threshold the first model explained 30.5% of the variance and the second model explained 43.4% of the variance. See Table 6 for the variance explained in the models for mathematics using state norming procedures. See Figure 1, Figure 2, and Figure 3 for the predicted values of proportion of identified students in mathematics across diverse schools using state norming procedures. The predicted values in Figure 1, Figure 2, and Figure 3 included all coefficients in the tables even those that were not statistically significant. The schools with the largest proportion of identified students were always urban or suburban schools while town and rural schools had the smallest proportion of identified students across varying levels of FRL and locale.

For the reading data set using a 5% state cut score, in the first step of the analysis about 16.6% of the variance was explained using only FRL as a predictor this model predicted that for a school at the grand mean of FRL students 2.6% of the student population would be identified as gifted. The second step of the model predicted that for a suburban school with the mean proportion of FRL, 1.82% would be identified as gifted. Adding locale codes and interaction terms explained 10% more variance than the first model. When a 10% statewide norming cut score was applied, the R^2 of the first model was .166 which indicated 16.6% of the variance could be explained. The second model explained 40.7% of the variance. When a 20% cut score was applied the R^2 of the second model was .545. See Table 7 for the variance explained in the models for reading using state norming procedures.

In both mathematics and reading, after increasing the cut score threshold from top 5% to 10% and later 20% the general trend was that proportion of FRL students to have a stronger impact on proportion of identified students. This was evidenced by the increasing strength of the correlation between proportion of identified students and proportion of FRL students, and in the increasingly negative coefficient of the FRL predictor in the regression models. In both subjects the most variance was able to be explained at the 20% threshold, which means that the proportion of identified students could be predicted most accurately knowing school-level variables and suggests an unequal distribution of identified students. This may seem counter intuitive at first since more children were identified using a 20% threshold rather than a 5% threshold, however the use of statewide norms resulted in a pattern where students at low-poverty schools were identified at a much higher rate than high-poverty schools, controlling for locale (see Figure 1, Figure 2, and Figure 3).

Research question 2. The second research question examined how much variability could be explained when implementing district norming procedures. he first model using a 5% district cut score in mathematics explained 7.4% of the variance. Upon adding dummy codes and interaction terms for locale, 16% of the variance could be explained by the model. It predicted 3.33% of students would be identified at a suburban school at the mean for FRL. The FRL slope was -.026 which predicted 2.6% fewer students to be identified at a suburban school 10% above the grand mean for FRL. At the 10% threshold for district norming in mathematics, the R^2 of the second model increased to .168. At the 20% threshold the R^2 increased to .192. See Table 8 for the variance explained in the models for mathematics using district norming procedures.

In the first step of the analysis for reading using the 5% district cut score the initial model explained 4.1% of the variance. Upon adding dummy codes for locale and interaction effects, the variance explained increased to 11.7%. For reading, when applying district norming procedures across each of the three thresholds the proportion of FRL students became a nonsignificant predictor. The R^2 in the second model increased to .181. When a 20% district norming threshold was applied the R^2 in the second model increased to .232. See Table 8 for the variance explained in the models for reading using district norming procedures. See Figure 4, Figure 5, and Figure 6 for the predicted values of proportion of identified students in reading across diverse schools using district norming procedures.

At the 20% threshold in both subjects the FRL slope became a nonsignificant predictor; this is desirable because it suggests that the proportion of FRL students a school has is not related to the proportion of identified students and making access to gifted education more equitable when compared to state norming procedures. Moving from state norms to district norms resulted in a drop in variance explained or R^2 at every threshold which indicated that school-level variables are less predictive of proportion of identified students. As can be seen in the predicted values charts, when compared to state norming procedures district norming identified higher rates of identified students due both to the increasing size of the intercept and the coefficient for FRL becoming less negative.

Research question 3. The third research question examined how much variability could be explained when implementing school norming procedures. When the top 5% in each school was used to generate the cut score, the first step in the analysis for mathematics explained about 3.7% of the variance in a model containing only the FRL predictor. Upon adding dummy codes for school locale, 2.0% more variance was explained. The new model predicted that for a suburban school with the mean proportion of FRL 3.48% of students would be identified as gifted. For every additional 10% of the student population that is FRL eligible above the grand mean the model predicted a 2.0% increase in identified students. See Table 9 for the variance explained in the models using school norming procedures. See Figure 7, Figure 8, and Figure 9 for the predicted values of proportion of identified students in mathematics across diverse schools using school norming procedures.

For the reading data set using a 5% school norming procedure, the second step of the regression model explained about 0.68% of the variance in proportion of identified students across the sample and the FRL slope was statistically nonsignificant. It predicted that for a suburban school with the mean proportion of FRL students, 2.8% would be identified as gifted. When a local norming was applied with a 10% threshold the first model explained 21.6% of the variance and the second model explained 34.1% of the variance. See Table 10 for the variance explained in the models for reading using school norming procedures.

In both subjects, not much variance was explained upon adding locale codes because in theory every schools should have 5%, 10% and 20% of students identified and thus there should be no variability to be explained. Both reading and mathematics had a statistically significant, positive FRL slopes. Which could be indicative of a skewed distribution or statistical artifact.

Research question 4. The fourth research question examined how many students would qualify for gifted services while scoring below proficiency standards when implementing school norming procedures. For the analysis on mathematics scores, when applying 5% school norming procedures 18 students out of 43,550 (0.04%) were identified as gifted and also scored below state proficiency standards. When the definition of the top 10% was applied, 154 (.2%) students were labeled as gifted with a mathematics RIT score below 208. When the top 20% in each school was applied 1650 (1.8%) students were labeled as gifted while scoring below proficiency standards. The number of students identified as gifted while scoring below proficiency standards in mathematics grouped by locale can be seen in Table 11.

For reading, when using the 5% threshold 9 out of 93,057 (0.01%) students in the state were labeled as gifted and had a RIT score below 205, the state proficiency standard for reading. For the 10% cut score, 86 (.10%) students, were labeled as gifted and were also scored below state proficiency standards, see Table 28. When using the 20% cut score, 1223 (1.3%) students were labeled as gifted with reading scores below proficiency level. The number of students identified as gifted while scoring below proficiency standards in mathematics grouped by locale can be seen in Table 12.

Research question 5. The fifth research question examined how larger the range of cut scores were within and between district when using school norming procedures. The first model for the mathematics data set using the 5% threshold the model predicted the population variance,

τ_{00}, as 30.63 which describes the variance of average cut scores between districts. The level one variance, σ^2, was 41.13 represented the variability in cut scores for schools in the same district. The ICC was .427 meaning 42.7% of the variance in cut scores was between districts, see Table 13. Next, I added the grand mean-centered FRL variable and ran a random coefficients regression model HLM. The FRL slope was -.17 which is interpreted as for each additional 10% a school was above the grand mean the model predicted the cut score to be 1.7 RIT units lower. Since the variance for the FRL slope was >.5 this indicates that the effect of FRL was the same for all schools. The σ^2 was 28.68, a reduction of 30.3% in level one variance. When applying a 20% threshold for school norming in the baseline HLM model the average district cut score decreased to 213.42 and the σ^2 increased to 36.04. After including FRL in the next step of the model the level one variance decreased by about 38%. The slope for FRL was -.18, similar to the slope in the fitted 5% cut score model.

The τ_{00} the baseline model for the reading data set utilizing a 5% threshold, was 19.61 and the σ^2 was 33.94, as can be seen in Table 33. The ICC was .366 meaning 36.6% of the variance in cut scores was between districts, see Table 14. After controlling for the effects of proportion of FRL students, τ_{00} decreased to 4.47 and the FRL slope, -.16, did not vary significantly among schools. In the top 20% cut score baseline model for reading τ_{00} was 29.82. After adding proportion of FRL students into the model 38.5% more variance of cut scores of schools in the same district could be explained.

In all analyses in both reading and mathematics, upon adding FRL one-third to one-half of the level one variance, representing variances between schools in the same district, was able to be explained In all the fitted models, there was not residual variance left to be explained in the FRL slope, meaning FRL had the same effect on building cut score at every school. In both reading and math, the FRL slope for both the 5% and 20% cut score thresholds were very similar, only varying by .01 or .02.

Discussion

Much like poverty, giftedness is a social construct, so there is a greater degree of control over its definition than naturally occurring phenomena. School norming procedures recognize the need for all students to be challenged in the classroom and the existence of a group of students at the upper tiers of academic achievement in all schools (Borland, 2004; Plucker et al., 2010). Analysis on the data suggested that when state or district procedures were applied there were inconsistent proportions of students identified across schools of varying proportions of FRL students and locale. Local norms resulted in the most equal distribution of proportion of identified students in schools across the state. When such norms were applied less than 2% of students in the state were identified as gifted in a subject without meeting minimal proficiency. When school norming was applied there was about as much variability within districts as between districts however, a large proportion of the variance was explained after adding school proportion of FRL into the models.

When using state norming procedures, the most variance was explained when using the 20% threshold and was had the highest correlation. This initially may seem surprising, since as the cut score threshold moved from 5% to 10% to 20% more students were identified however these students were disproportionally identified in schools with low proportions of FRL students. Explaining almost half of the variance in proportion of gifted students is not desirable because it suggests that the proportion of identified students can be predicted knowing school-level variables and thus an unequal distribution of identified gifted students across diverse schools. Using stringent cut scores can result in skewed identification practices because, as has been stated in the literature review, students who come from high-income families or who have highly involved parents do better on academic measures of achievement (Colgren & Sappington, 2015; Entwisle & Alexander, 1999; Hardesty et al., 2014; Michelmore & Dynarski, 2016; Reardon, 2011; Subotnik, Olszewski-Kubilius, & Worrell, 2011). Thus, strict norming procedures puts students who have had more access to learning opportunities both in the home and at school at an advantage to the expense of similarly talented, economically disadvantaged students (Berliner, 2009; Entwisle & Alexander, 1999; Olszewski-Kubilius & Clarenbach, 2012; Olszewski-Kubilius & Thomson, 2010).

Once district norming procedures were applied, the variance explained decreased substantially. However, proportion of FRL students was still a statistically significant, negative predictor of proportion of identified students when using 5% and 10% thresholds in mathematics and when using a 5% threshold in reading. Suggesting fewer students in low-poverty schools would receive similar educational opportunities via gifted education as their higher SES peers. Currently, in low-poverty schools 12.4% of students are involved in gifted programs while only 6.1% of students in high-poverty schools have access to such services (Yalma & Tyner, 2018). This trend can be seen in the predicted values for district norming. More students were identified in low-poverty school than in high-poverty schools and the distribution of identified students was uneven between school locales. Unequal access to gifted services may foster social inequalities by restricting access to appropriately challenging curricula that is above the level of their peers in the same class; these students may then fail to fully develop their talents and not be prepared for the rigor of challenging secondary course work (Olszewski-Kubilius & Clarenbach, 2012; Subotnik et al., 2011; Yalma & Tyner, 2018).

The use of local school norming procedures would in theory allow more children in diverse schools to have access to curricula that is in better alignment with their current academic ability.

Stemming from an approach in which the purpose of providing gifted services is to identify students who have surpassed the cognitive development of their in-class peers and provide them with more advanced and individualized instruction and curricular support (Barnett & Durden, 1993; Dai & Chen, 2013; Subotnik et al., 2011). It is widely accepted by scholars that all children, regardless of ability level, need to be challenged by their curriculum in order to continually improve their academic performance (Callahan & Miller, 2005; Reis & Renzulli, 2010; Subotnik et al., 2011). There is also evidence that differentiation in the general classroom is an ineffective method of gifted identification (Hertberg-Davis, 2009; Reis, Gentry, & Maxfield, 1998; Reis & Renzulli, 2010).

Speculation about academic potential is most defensible when made in comparison to the skills of other students who have had similar learning opportunities and life experiences. While group-specific norms may be the best way to account for differences in opportunities to learn, it is a controversial practice and significant variation exists within a single income grouping (Peters & Engerrand, 2016; Peters & Gentry, 2012). Most school districts assign students to schools based on where they live, so students in the same school are likely to share some of the same context, thus using local norms is more likely to reflect past educational opportunities of any one student in that school than national norms or district norms. This process is called frontloading and helps prepare students to succeed in future programs for gifted individuals such as Advanced Placement and International Baccalaureate courses (Olszewski-Kubilius & Clarenbach, 2012). It has also been suggested that use of local, school norming as well as universal screening could increase participation of historically underrepresented groups in gifted education (McBee, 2010; Olszewski-Kubilius & Clarenbach, 2012; Peters et al., In Press; Yalma & Tyner, 2018). School building norming may help to enhance the ability of schools to be social equalizers and help develop the talent of all students equally regardless of school-level variables (Entwisle & Alexander, 1999). As a function of treating all schools equally identification rates were roughly equal across FRL proportions and school locales at each threshold. In both reading and mathematics, at the 20% building norms threshold, proportion of FRL students was statistically significant and positive; this was strange because I set all the schools in the sample to have the same proportion of identified students so a correlation should not exist. This finding could suggest a non-normal distribution of scores or statistical artifact.

One potential drawback to utilizing school norming for gifted identification is that students could be labeled as gifted in a subject without meeting minimum proficiency. In a multi-state analysis of gifted policy, all five states in the study required students to meet minimum proficiency to be considered gifted (Brown et al., 2006). If states required students to meet minimum proficiency in order to receive gifted services, this would result in introducing additional educational inequities most likely to affect high-poverty schools. However, this may not need to be the case, the Revolving Door Identification and Programming model (RDIM) employs flexible methods of identification and offers a continuum of services based on the needs of the students it serves (Housand, 2008; Reis & Renzulli, 2010; Renzulli & Reis, 1994; Delisle, Reis, & Gubbins, 1981). The flexibility in the gifted services provided would be key for students scoring below proficiency level and receiving gifted services. For example, it may mean that an intermediary mathematics class for such students may need to be developed so that they receive instruction that is more aligned with their current level of academic ability. In such a case the emphasis is placed on meeting the educational needs of the students rather than the “giftedness” of such students.

No matter what threshold was utilized, when implementing school norming procedures there was about as much variability in cut scores within districts as between districts. This could be potentially confusing if students are labeled as gifted at one school but are not considered gifted at a neighboring school. If parents or the community view identification practices as arbitrary they will likely oppose funding for such services (Renzulli, 1984). However, if the policies concerning gifted education emphasize the need to identify students for whom the general education classroom is not sufficient for their level of development, it is reasonable that in one school a child may need gifted services and in another setting the student may be adequately challenged in the general education class. This would be particularly true if a student moved from a high-poverty school to a low-poverty school. The fact that entering the FRL predictor at level one in the HLM models reduced one-third to one-half of the level one variance in cut score is indicative of how student context impacts the level of achievement students can achieve.

Limitations

All research has limitations that must be discussed when considering the implications of the study. This study was based on the analysis of data from a single state and it is unknown whether results would generalize to other states. There were also variables missing in both data sets which brings up concerns of attrition. In both the reading and mathematics samples, over 88% of the students came from either urban or suburban schools. Thus, additional studies should examine rural and town districts to determine if results generalize. Finally, this study was descriptive and hypothetical in nature and largely overlooked the challenges of implementing such a program in real schools.

Conclusion

Several scholars have suggested that access to appropriately challenging curricula contributes to high academic achievement. Yet, if children are required to score higher on standardized tests than is reasonable given their prior educational opportunities in order to receive gifted services they may fail be challenged by their schoolwork (Matthews & Foster, 2005; Reis, Hebert, Diaz, Maxfield, & Ratley, 1995; Tomlinson & Jarvis, 2014). Low educational attainment limits access to well-paying employment and thus the cycle of poverty is likely to repeat itself (Chetty, Friedman, and Rockoff, 2011; Duncan & Magnuson, 2011; Entwisle & Alexander, 1999; Owens, 2010; Yalma & Tyner, 2018). Numerous studies have suggested many gifted students fail to be challenged in the general classroom, especially in high-poverty schools (Macrae & Lupart, 1991; Olszewski-Kubilius & Clarenbach, 2012; Peters et al., 2017; Reis & Renzulli, 2010). This is arguably more of a problem in high-poverty schools; one can argue school effectiveness is more important for low SES students to learn the skills that will allow them to become competitive in the labor market than for high SES students, as evidence by the differential rates of achievement upon kindergarten entry. High SES parents tend to have the resources and knowledge to promote cognitive development in their children, while many low SES parents do not likely due in part to the stresses of economic strain. The variance at the aggregate level of achievement between schools should be viewed as irrelevant to gifted identification. For example, the overall achievement at a low-poverty school will likely be higher than the achievement at a high-poverty school, yet in both schools there exists a group of students who will require additional educational opportunities, beyond those provided to the general school population, in order to be educated to their highest potential (Callahan & Miller, 2005; Hamilton et al., 2017; Renzulli, 1984). (Callahan & Miller, 2005; Hamilton et al., 2017; Renzulli, 1984) Upon implementing school-based norming procedures school locale and proportion of FRL students did not predict proportion of identified gifted students. Implementing school norms in this state would help better foster the academic talent of economically disadvantaged students, particularly in high-poverty schools.

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Appendix A

Table 1

Descriptive statistics of the sample for reading grouped by locale

Locale	Districts *N*	Schools *N*	Students *N*	Mean proportion FRL
City	87	614	40,871	80.52
Suburban	223	531	41,571	47.31
Town	42	57	4,219	58.97
Rural	88	104	5,094	41.76
Locale missing	18	27	1,302	0.00

Table 2 *Descriptive statistics of the sample for reading grouped by locale*

Locale	Districts *N*	Schools *N*	Students *N*	Mean proportion FRL
City	88	671	41,273	80.53
Suburban	224	571	41,926	47.37
Town	43	64	4,232	58.97
Rural	88	106	5,104	41.76
Locale missing	15	19	1,015	0.00

Table 3

Bivariate correlations between proportion of free and reduced lunch students (FRL) and proportion of identified students in mathematics

Threshold applied	Correlation
State 5%	-.409**
State 10%	-.463**
State 20%	-.549**
District 5%	-.270**
District 10%	-.279**
District 20%	-.289**
School 5%	-.191**
School 10%	-.038
School 20%	.203**

Note: *p < .05; **p < .001

Table 4

Bivariate correlations between FRL and proportion of identified students in reading

Threshold applied	Correlation
State 5%	-.406**
State 10%	-.540**
State 20%	-.664**
District 5%	-.217**
District 10%	-.276**
District 20%	-.322**
School 5%	-.016
School 10%	.159**
School 20%	.337**

Note: *p < .05; **p < .001

Table 5

Proportion of variance explained predicting proportion of identified gifted students in mathematics using state norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
State 5%	16.8%	27.3%
State 10%	21.6%	34.1%
State 20%	30.5%	43.4%

Table 6

Proportion of variance explained predicting proportion of identified gifted students in reading using state norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
State 5%	16.6%	26.6%
State 10%	29.5%	40.7%
State 20%	44.5%	54.5%

Table 7

Proportion of variance explained predicting proportion of identified gifted students in mathematics using district norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
District 5%	7.4%	16.0%
State 10%	7.9%	16.8%
State 20%	8.5%	19.2%

Table 8

Proportion of variance explained predicting proportion of identified gifted students in reading using district norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
District 5%	4.1%	11.7%
State 10%	7.1%	18.1%
State 20%	9.6%	23.2%

Table 9

Proportion of variance explained predicting proportion of identified gifted students in mathematics using school norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
District 5%	3.7%	5.7%
State 10%	.15%	1.5%
State 20%	4.2%	4.3%

Table 10

Proportion of variance explained predicting proportion of identified gifted students in reading using school norming procedures

Threshold applied	Variance in cut score between districts	Variance in cut score within districts	Reduction in level one variance after controlling for FRL
School 5%	36.6%	63.4%	34.4%
School 20%	40.9%	59.1%	44.9%

Table 11

Students below proficiency level identified as gifted in mathematics using state norming procedures grouped by locale

Threshold applied	Number of suburban students	Number of urban students	Number of town students	Number of rural students
State 5%	0	18	0	0
State 10%	42	111	1	0
State 20%	656	895	51	21

Table 12

Students below proficiency level identified as gifted in reading using state norming procedures grouped by locale

Threshold applied	Number of suburban students	Number of urban students	Number of town students	Number of rural students
State 5%	0	8	0	0
State 10%	15	69	0	0
State 20%	454	718	21	10

Table 13

Proportion of variance within and between districts in mathematics using school norming procedures

Threshold applied	Variance in cut score between districts	Variance in cut score within districts	Reduction in level one variance after controlling for FRL
School 5%	42.7%	57.3%	30.3%
School 20%	45.3%	54.7%	43.4%

Table 14

Proportion of variance within and between districts in reading using school norming procedures

Threshold applied	R^2 with FRL only	R^2 with FRL and locale
State 5%	16.8%	27.3%
State 10%	21.6%	34.1%
State 20%	30.5%	43.4%

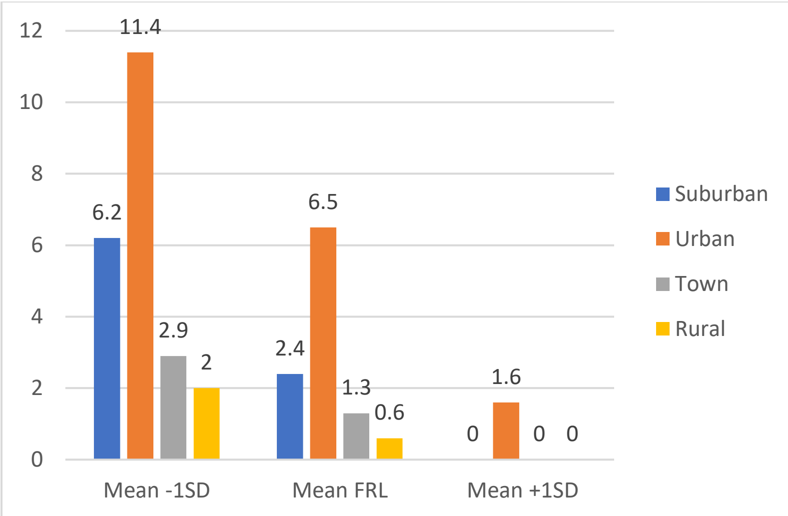

Figure 1. Predicted proportions of students identified grouped by locale using top 5% of statewide norms in mathematics

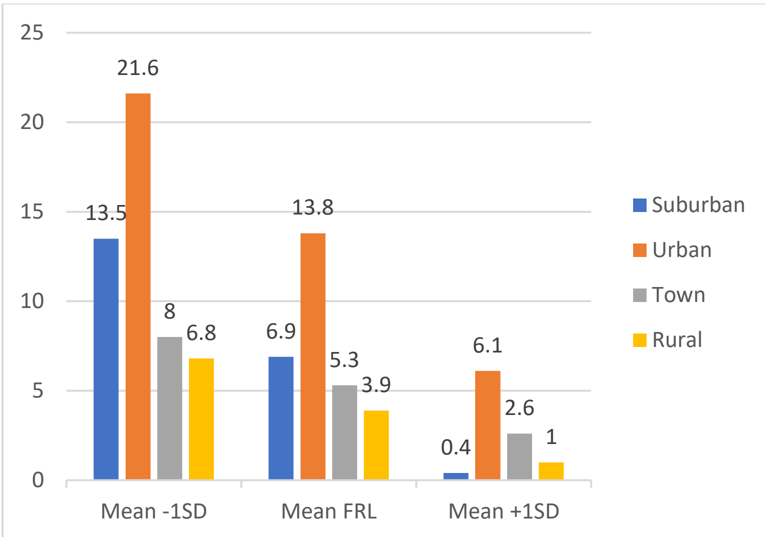

Figure 2. Predicted proportions of students identified divided by locale using top 10% of statewide norms in mathematics

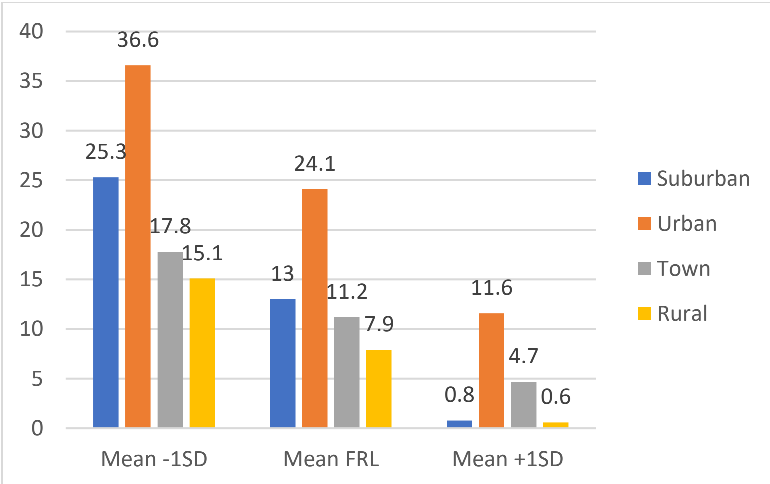

Figure 3. Predicted proportions of students identified divided by locale using top 20% of statewide norms in mathematics

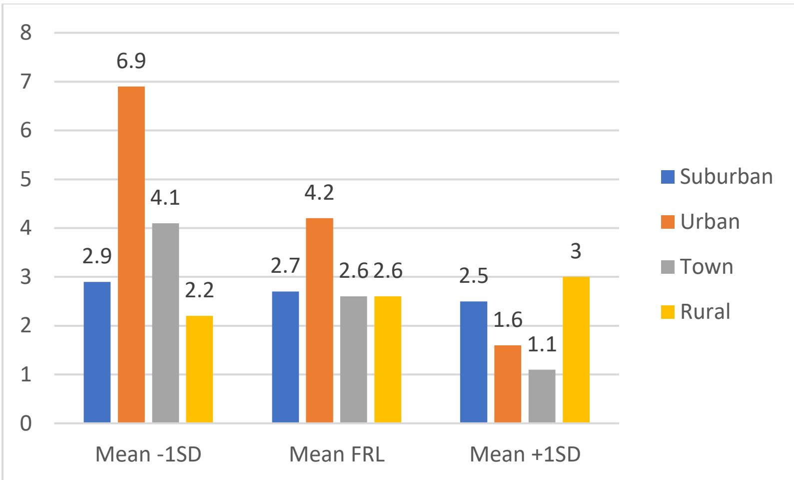

Figure 4. Predicted proportions of students identified grouped by locale using top 5% of district norms in reading

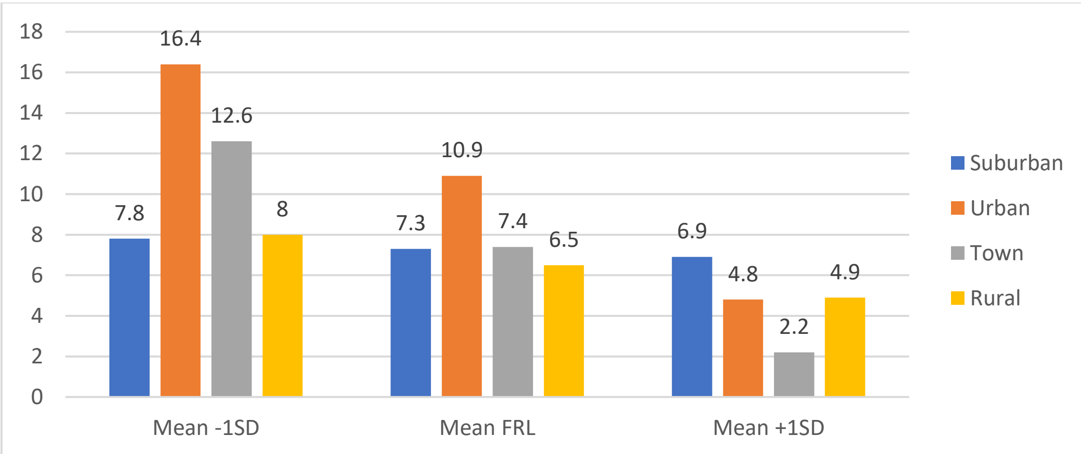

Figure 5. Predicted proportions of students identified grouped by locale using top 10% of district norms in reading

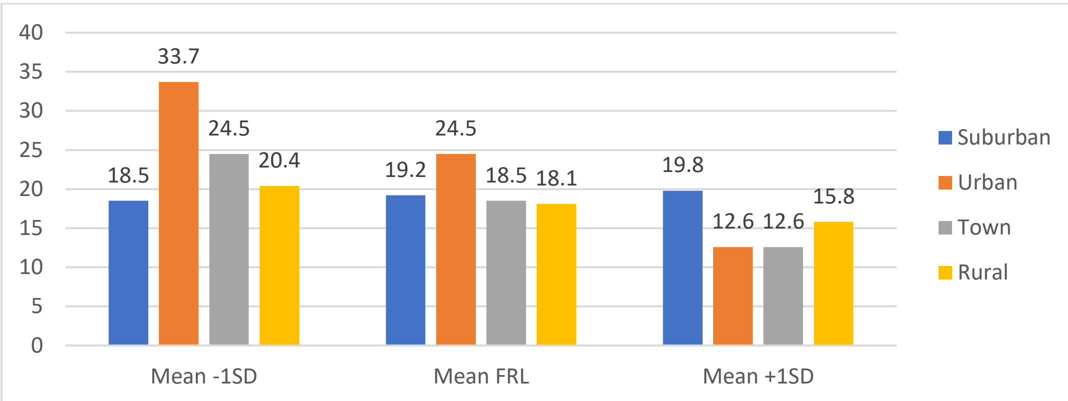

Figure 6. Predicted proportions of students identified grouped by locale using top 20% of district norms in reading

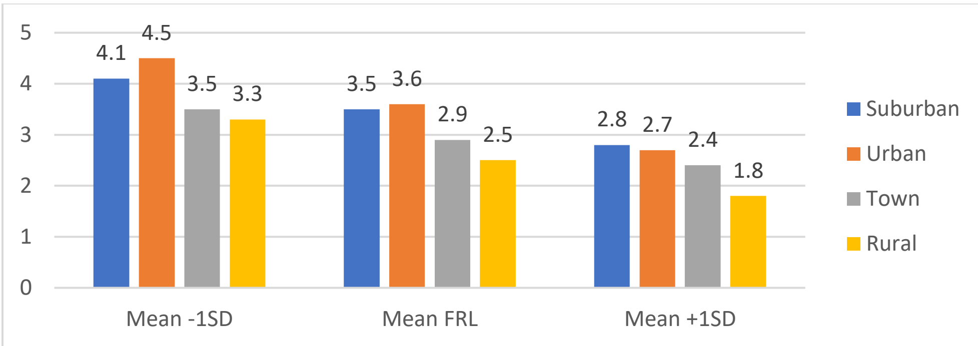

Figure 7. Predicted proportions of students identified grouped by locale using top 5% of school norms in mathematics

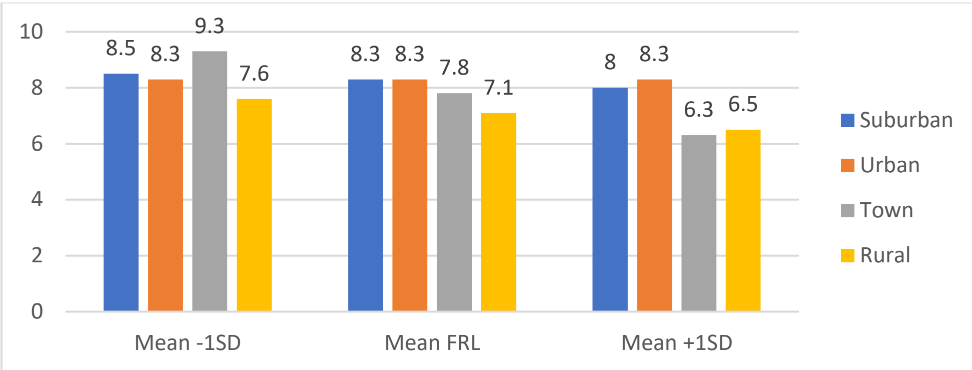

Figure 8. Predicted proportions of students identified grouped by locale using top 10% of school norms in mathematics