Article

Gifted Child Quarterly
1–20

DOI: 10.1177/0016986219830768
journals.sagepub.com/home/gcq
SAGE

Inequities of Enrollment in Gifted Education: A Statewide Application of the 20% Equity Allowance Formula

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Abstract

Underrepresentation in gifted education for ethnically diverse student groups has been widely recognized. Two recent federal district court decisions defined the lower limits of equitable participation using the 20% equity allowance formula proposed by Donna Ford. The purpose of this article was to evaluate the application of the 20% rule to identify the prevalence of inequity and associated variables in Texas gifted education programs. Using data from the Office of Civil Rights and Texas Education Agency, the authors applied the 20% rule to demographics of K-12 gifted education programs in Texas to identify inequity and used Bayesian regression with district characteristics to investigate contributing factors of inequity. Only 282 of 994 (28.4%) districts met equity standards for Hispanic students. Second, Bayesian regressions with district-level characteristics of students, teachers, and expenditures were used to identify factors associated with inequitable enrollment of Hispanic students. Overall, the model accounted for 12.9% variance (R^2 = 0.129, 95% highest density interval [0.095, 0.170]), with increasing variance explained by district subsets (i.e., city, suburb, town, rural). Furthermore, the results of the regression models revealed the percentage of Hispanic and White teachers were inversely associated with inequity across all district subsets. It is postulated that the mechanism of inequity is in the teacher referral process, frequently used as a determinant of gifted education enrollment. The authors suggest means of addressing this reality.

Keywords

gifted education, multicultural, equity, identification, Bayesian

Although there is no federal mandate for gifted and talented (GT) education in the United States, 32 states have policies requiring identification and/or academic services for GT students, and approximately three million students in the United States have been identified for participation in gifted education (National Association for Gifted Children [NAGC] & Council of State Directors of Programs for the Gifted [CSDPG], 2015). However, underrepresentation, also referred to in this study as inequitable enrollment, and equity issues continue to plague the field of gifted education (Borland, 2008; Ford, 2010, 2015; Ford & Grantham, 2003; Frasier et al., 1995; Gentry, Hu, & Thomas, 2008; Grissom & Redding, 2016; McBee, 2006; Olszewski-Kubilius & Thomson, 2010; Siegle et al., 2016; Yoon & Gentry, 2009). In the U.S. public educational system, White students make up approximately 50.4% of the student population, but 58.2% make up GT program enrollment. Asian students make up 4.8% of the total U.S. student population and 9.9% of GT enrollment. Conversely, 24.8% and 15.5% of the U.S. student population is composed of Hispanic and Black students respectively, with only 18% of Hispanic students and 9.9% of Black students enrolled in GT programs. The issue of over- and underrepresentation extends to Advanced Placement (AP) courses as well. 57.3% of students and 10.7% of students enrolled in at least one AP course are White and Asian respectively across the United States, whereas 19.6% and 9.2% of students enrolled are Hispanic and Black in at least one AP course respectively. Recently, Yaluma and Tyner (2018) investigated access and participation in gifted programs by various student groups, particularly high-poverty areas, across the nation using data from OCR, the National Center for Education Statistics (NCES), and the National Assessment of Educational Progress. When looking at GT participation by race and ethnicity, they found that GT program participation of Black and Hispanic students was consistently lower than Asian and White students across the nation. For instance, Asian students made up 4.8% of the overall student population and 8.6% were enrolled in GT programs, Black students made up 15% of the student

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population with 10% enrolled in GT programs, Hispanic students made up 27.6% of the overall student population, and 20.8% were enrolled in GT programs, and White students made up 47.9% of the student population with 55.2% enrolled in GT programs. Yaluma and Tyner (2018) also investigated enrollment across low-, moderate-, and high-poverty areas and found overrepresentation of Asian and White students in school districts in moderate- to high-poverty areas, but identified overrepresentation of Asian students only in low-poverty areas. They also found that these results vary by state (Yaluma & Tyner, 2018), further highlighting the ongoing issue of race, poverty, and equity in gifted education.

Black and Hispanic students have been underrepresented in gifted education programs, AP programs, and International Baccalaureate programs consistently for years, even decades (Ford, 2013c; Peters & Engerrand, 2016; Yoon & Gentry, 2009). In 2011, Ford argued that underrepresentation was the most pressing problem facing gifted education in the United States, a problem that has been studied and continues to be emphasized by many others. In fact, in 2014 to 2018 alone, diversity and equity research trended in the field of gifted education with over 15,000 hits in Google Scholar using the phrase "equity in gifted education U.S." and over 15,000 hits with the phrase "excellence gaps in gifted education U.S." Perhaps more interesting is the number of hits when using phrases that target specific solutions and recommendations provided by the field: "universal screening gifted education U.S." (16,100 hits), "teacher referral gifted education U.S." (7,640 hits), and "locally normed gifted education U.S." (1,550 hits). Why is it that schools continue to struggle with equitable representation of student populations in GT services amid a vast sea of information, and what might induce necessary change?

Where Have We Been? A Snapshot of Equity in Gifted Education

In 1972, Sidney Marland Jr. addressed the state of gifted education in the United States, lighting the beacons for stakeholders to regard diversity in GT education stating, "Gifted children exist within all levels of society, within all racial and ethnic groups, and they come from every kind of home. Any programs to develop their talents must be concerned with their diversity" (p. 99). Following Marland's report, congress passed the Gifted and Talented Children's Education Act (1978) authorizing the use of federal funds to support programs in gifted education (Russo, 2001). In 1988, the Jacob K. Javits Gifted and Talented Students Education Act was introduced to help schools at the state and local levels to identify GT students and provide students with appropriate educational services. This act, reauthorized in 1994 (Russo, 2001) and most recently in 2015 (NAGC, n.d.-b), also prioritized the identification of traditionally underrepresented students, economically disadvantaged students, English language learners, and students with learning disabilities in gifted research and program services (U.S. Department of Education, n.d.). However, the Javits Act primarily focuses on funding and does not address the protection of gifted students' legal rights; therefore, issues pertaining to students' rights in gifted education are addressed within state laws (Russo, 2001; Zirkel, 2004, 2005). It is perhaps this variation across state regulations and statutes, variation within concepts and state-held definitions of giftedness, and the students served within those states that make equity issues most difficult to investigate.

Inquiry and investigation of issues regarding identification of student groups who have been historically underrepresented permeate gifted education research. In 1995, Frasier, Passow, and Garcia examined assessment issues in gifted education and suggested three primary reasons for underrepresentation: (a) test bias, (b) selective referrals, and (c) deficit-based paradigms, topics the field continues to wrestle with over two decades later. Others have affirmed that research regarding underrepresentation in gifted education has typically examined assessment and identification issues largely because "traditional approaches are widely perceived to be highly biased" against historically underrepresented student groups such as American Indian, Black, Hispanic, and students from socioeconomically disadvantaged backgrounds (Cao, Jung, & Lee, 2017; Plucker & Callahan, 2014, p. 395). Though debates surrounding these issues remain (Hodges, Tay, Maeda, & Gentry, 2018), we have made promising steps in the area of more inclusive identification procedures (Plucker & Callahan, 2014). For instance, some researchers have sought to clarify questions in the field such as identification, assessment, and the current state of equity in gifted education (i.e., Cao et al., 2017; Ford, Grantham, & Whiting, 2008; Goings & Ford, 2018; Hodges et al., 2018; Olszewski-Kubilius & Corwith, 2018; Zirkel, 2016), whereas others have challenged withstanding traditional beliefs and practices in gifted education by emphasizing more inclusive identification and participation in gifted education programs (Peters, McCoach, McBee, & Matthews, 2014; Plucker & Callahan, 2014).

Methods of Identification

Definitions of giftedness and identification of students for GT programming is not consistent across states (Hodges et al., 2018; NAGC & CSDPG, 2015) with some requiring strict adherence to state definitions (i.e., Pennsylvania and South Carolina) and/or the use of standardized assessments (i.e., Arizona and South Carolina) and other states allowing each district to decide criteria for enrollment in gifted programs (i.e., Texas and Wisconsin) (NAGC & CSDPG, 2015). Most schools across the United States use standardized tests and teacher referrals to identify gifted students, with teacher referrals often carried out as the initial step in the identification process (Miller, 2009). The first requirement for enrollment in any program is acceptance into that program.

Therefore, the mechanism of inequity may be partially the result of the identification process used.

Standardized Tests. Underrepresentation of ethnically diverse students has been widely demonstrated as exemplified by just a handful of studies mentioned previously; however, mechanisms of inequity are a bit more nuanced and complex. Some suggest that underrepresentation in gifted programs results from lower test scores obtained by Native American, Black, and Hispanic students as compared with their White and Asian peers (Ford, 2005; Frasier et al., 1995). Peters and Engerrand (2016) examined data from the Wisconsin Knowledge and Concepts Examination (Math), the National Assessment of Educational Progress, and the Cognitive Abilities Test (CogAT) and found that consistently across all measures, Black, Hispanic, and Native American students scored 0.13 to 1.04 standard deviation units lower than similarly aged White students. Similarly, Giessman, Gambrell, and Stebbins (2013) found that Black and Hispanic students scored from 0.69 to 1.07 standard deviation units lower than White students on the CogAT composite. Using just the CogAT nonverbal and the Naglieri Nonverbal Ability Test (2nd ed.), Black and Hispanic students still scored from 0.38 to 1.07 standard deviation units lower than similarly aged White students (Giessman et al., 2013). Returning to the meta-analysis by Hodges et al. (2018), they compared traditional and nontraditional identification methods (this included the assessment and procedures) used. Nontraditional methods included the Raven Standard Progressive Matrices, the Naglieri Nonverbal Abilities Test, and the CogAT-Nonverbal (CogAT-NV) contrary to traditional methods such as IQ tests and achievement tests. They found that Hispanic, Native American, and Black students were one-third less likely to be identified as gifted regardless of the identification instrument (Hodges et al., 2018).

Differential performance on standardized tests by race/ethnicity has been found to exist (Giessman et al., 2013; Hodges et al., 2018; Peters & Engerrand, 2016). Test bias is often to blame for such discrepancies; however, several alternative explanations have been offered for race/ethnicity differences in standardized test scores (Peters & Engerrand, 2016) which have included systematic issues such as inequality in educational opportunity (Erwin & Worrell, 2012; Worrell, 2015). In fact, Erwin and Worrell (2012) advised against sustained attention on test biases as a mechanism of racism and underrepresentation as it detracts our attention from the root of the issue: the achievement gap. Why? Because blaming differential performance on test bias ignores serious differences in educational opportunities that result in differential performance. Instead, they encourage work in policy reform as the vehicle to increase equity in GT programs.

Nominations. Teacher and parent referrals/recommendations, also referred to as nominations, can serve a critical role in the gifted identification process (Miller, 2009; Siegle et al., 2010) and have been highlighted as a potential concern regarding underrepresentation in GT programs (Card & Giuliano, 2015; Ford et al., 2008; Olszewski-Kubilius & Corwith, 2018). With the nomination process, parents or teachers can nominate, or refer, students for GT screening and enrollment.

Factors linked to the teacher nomination/underrepresentation issue include teacher beliefs about giftedness (Miller, 2009; Olszewski-Kubilius & Corwith, 2018) and teacher and parent perceptions regarding student abilities, especially the abilities of students from poor and immigrant family backgrounds (Card & Giuliano, 2015). For example, when considering factors affecting teacher nominations, Siegle et al. (2010) found that student interests, domain-specific strengths (such as advanced levels of reading), and personality characteristics affected the rate of teacher referral for gifted identification. In another study, after controlling for background variables such as socioeconomic status and school/classroom characteristics, Grissom and Redding (2016) found that both Hispanic and Black students were less likely to be assigned to gifted programs with Black students even more so. However, when they accounted for academic ability, the discrepancy for Hispanic students disappeared. In other words, the probability of GT enrollment was the same when considering a Hispanic student and White student of equal academic ability. They also found that Black students taught by non-Black teachers (2.1%) were less likely to receive referrals for gifted programs as compared with Black students taught by Black teachers (6.2%; Grissom & Redding, 2016). Subsequently, in another study, findings supported greater representation of Black students in gifted education programs in schools with larger numbers of Black teachers or schools that had a Black principal (Grissom, Rodriguez, & Kern, 2017). They found a similar (nearly identical) relationship for Hispanic students.

In 2006, McBee examined nomination/referral resources (i.e., teacher, parent, and automatic) in gifted programming in the state of Georgia using the phi coefficient to measure the association between nomination status and a student's status as gifted. When examining the strength of this association, he found that teacher nominations for Black and Hispanic students did not function as well as those nominations given for their Asian, Native American, and White peers. Parent nominations were found to be equally as effective for Asian, Black, and Hispanic students but performed better for Native American and White students. Parent nominations also occurred more frequently for Asian, Native American, and White students than they did for Black and Hispanic students. Additionally, automatic referrals, or referrals that automatically take place as a "student scores in the 90th percentile or higher on a standardized test" were equally as effective across all student groups, and teacher referrals were highly associated with placement in GT, second to automatic referrals (McBee, 2006, p. 105). However, McBee

(2006) warned that investigations of the relationship between teacher referral and student race should control for other variables as well, such as socioeconomic status and mastery of English, because these lurking variables that can be associated with both teacher referral and student race may explain differences in nomination rather than student race alone. Grissom et al. (2017) echo this same sentiment—how does one decipher whether teacher bias is at play or a more accurate depiction of student ability? Furthermore, Yaluma and Tyner (2018) state,

> while teacher nominations are a good mechanism for identifying students who may benefit from gifted programming but do not meet the testing cutoff, relying primarily on parent and teacher nominations, as happens in many schools, is prone to bias, favoritism, and abuse. (p. 22)

Indeed, although discrepancies in the nomination process between teacher and student race exist, it is difficult to tease out the exact mechanism taking place during the referral process looking at numbers alone.

Multiple Criteria. Considering the relationship between standardized test scores and inequality of recommendations to participate in GT programs, some caution against the reliance of a single identification method (Erwin & Worrell, 2012; Peters & Engerrand, 2016; Yaluma & Tyner, 2018) and advocate for more holistic assessment protocols that consider multiple and varied data capable of better contextualizing an assessment (Grissom et al., 2017; Johnsen, 2011; NAGC, 2010; Peters & Engerrand, 2016; Yaluma & Tyner, 2018). For instance, Johnsen (2018) recommends a case study protocol that includes a variety of data sources that are quantitative and qualitative, as well as verbal and nonverbal reasoning measures, and organizes information to capture both strengths and weaknesses of the student. Erwin and Worrell (2012) recommend multiple criteria as best practice for gifted identification asserting that previous achievement is the best predictor of a student's future achievement, and IQ score as the next best predictor. They also suggest domain-specific performance tasks as a practical addition to identification practices in GT enrollment; however, "there is little evidence that these tasks add incremental validity beyond commonly used IQ tests and indicators of previous achievement" (Erwin & Worrell, 2012, p. 80). Other researchers raise considerable questions and have called for more investigations regarding the use of multiple criteria raising questions such as: (a) Which instruments or methods should be used for identification? and (b) How should the information from multiple measures (with possible contradictions) be combined? (Cao et al., 2017). As multiple criteria seem to be the most recommended approach to increase equity (i.e., Erwin & Worrell, 2012; NAGC, n.d.-a; Peters & Engerrand, 2016; Yaluma & Tyner, 2018), the mechanisms within this process provide further questions to be addressed by the field.

Universal Screening and Local Norms. Universal screening has shown increases in gifted programming for ethnically diverse students and English language learners (Card & Giuliano, 2015) as well as students living in low socioeconomic conditions and female students (Yaluma & Tyner, 2018). However, Lakin (2016) cautioned against the widespread acceptance of universal screening, suggesting that more research ought to investigate the effects of universal screening on students' diversity when common cutoff scores are employed. Yaluma and Tyner (2018) also suggested the use of local norms as an effective way to identify students for gifted programs, further recommending that larger school districts should identify at the school level. Similarly, Peters and Engerrand (2016) recommended using group-specific norms with local norms and universal screening to encourage equity in gifted programs and the preservation of the purpose or function of gifted education.

Metrics of Identification

Underrepresentation of ethnically diverse students in gifted education has been examined in a variety of ways. In 2009, Yoon and Gentry evaluated the overrepresentation of Asian American students in gifted programs using the representation index (RI). They define RI as the "ratio of the proportion of students from a given racial category in gifted programs to the proportion of students from that given racial category in schools with the gifted programs" (p. 125). An RI of 1.0 indicates a perfect proportion. Anything above 1.0 begins to indicate overrepresentation, and anything less than 1.0 begins to indicate underrepresentation. Using this method, Yoon and Gentry (2009) found overrepresentation of Asian and Pacific Islander students in 41 states and underrepresentation of Hispanic students (43 states) and Black students (42 states). More recently, Hodges et al. (2018) conducted a meta-analysis to examine underrepresentation and the identification methods used in gifted programs within the United States. They used a risk ratio which compares the occurrence of identified gifted students in the focal group to that of the reference group and found that Black, Hispanic, and Native American students were approximately one-third less likely to be identified than Asian or White students (Hodges et al., 2018). Wright, Ford, and Young (2017) used the Relative Difference in Composition Index (RDCI), a discrepancy index to quantify the difference between a racial groups' gifted education composition and their general education composition. The RDCI is a ratio expressing the "relative difference between the proportion of students with a particular characteristic, condition, or discipline outcome and the representation of these students within the total student population" (Nishioka, 2017, p. 12). The RDCI is calculated as follows:

$$\mathrm{RDCI} = \left(\frac{\begin{array}{c}\text{Percent of group of interest}(\mathrm{GT}) - \\ \text{Percent of group in total population}\end{array}}{\text{Percent of group in total population}} \right) 100$$

For example, if 25% of students in a GT program were Hispanic and 45% of students in the total student body were Hispanic, then

$$\text{RDCI} = \left(\frac{\begin{array}{c}\text{Percent of Hispanic Students in GT}(25\%) - \\ \text{Percent of Hispanic Students in Total}(45\%)\end{array}}{\text{Percent of Hispanic Students in Total}(45\%)} \right) 100$$

$$= \left(\frac{25-45}{45} \right) 100 = (-0.4444)100 = -44.44.$$

In the RDCI calculation, negative RDCI values indicate underrepresentation and positive values indicate overrepresentation. An RDCI value of zero indicates perfect representation, and the greater distance from zero, positive or negative, indicates the magnitude of the RDCI.

Using the Office of Civil Rights (OCR) education data between the years 2006 and 2011, Black student underrepresentation in gifted education ranged from RDCI = −43 to −47 across the United States (Wright et al., 2017). The same OCR data indicated that between the years 2006 and 2011, Hispanic student underrepresentation in gifted education ranged from RDCI = −31 to −37. However, it is important to note here that Wright et al. (2017) state, "used in a decontextualized way, the RDCI is insufficient for determining inequitable and/or discriminatory under-representation" (p. 54), which leads to their advocation to use an equity formula proposed by Ford (2013b), the lens through which equity is later analyzed in the current study.

Considering Equity Through the Lens of the Equity Allowance Formula

Ford (2013b) defined an equity threshold in which equitable representation in gifted education could be assumed if a race/ethnicity group's proportional representation in the gifted education program is at least 80% of the group's total representation in the student population of the school or school system (Wright et al., 2017). The designated 20% allowance accounts for chance factors such as, human error, attitudes, or dispositions; assessment protocols and policies; and measurement instruments with potential bias that might affect participation in the GT program (Ford, 2013b; Wright et al., 2017). However, when participation in the GT program for a group falls below the equity allowance (commonly referred to as the 20% rule), the inequality is thought to exist "beyond statistical chance" or beyond chance factors (Wright et al., 2017, p. 53). The equity allowance formula was designed to address the following questions: (a) When is underrepresentation significant? (b) How severe must underrepresentation be in order to require changes? and (c) How severe must underrepresentation be to be considered discriminatory? (Wright et al., 2017, p. 54). Moreover, Wright et al. (2017) assert that the 20% equity allowance formula is a "quantifiable metric that accounts for differences and injustices, thereby opening doors for many non-White students who might otherwise not be identified and served in gifted education. Moreover, the formula safeguards claims of ignorance that typically can be described as indifference to those who are not part of the status quo" (Wright et al., 2017, p. 56); yet, empirically, limited research exists regarding the practical application of the rule. For the purposes of this study, inequitable enrollment refers to underrepresentation, and equitable access to gifted services is explored and evaluated by Ford's equity formula.

The 20% equity allowance in gifted education was discussed in the U.S. District Court system. In *McFadden v. Board of Education for Illinois School District U-46* (2013), the court ruled in favor of the plaintiff finding that the district's GT program unlawfully discriminated against Hispanic students (see Peters & Engerrand, 2016). Specifically, District U-46 was found to inequitably identify Hispanic students to participate in the gifted education program. District Judge Gettleman explained, "Although the District takes issue with some of the methodology used by the plaintiffs in offering these statistics, there is no doubt that Minority Students do not participate in the mainstream gifted programs in District U-46 at anything close to their proportion in the District's population" (*McFadden v. Board of Education*, 2013, p. 900).

What constitutes inequitable enrollment in gifted education remains a viable and important question. In District U-46, 43.8% of the students were Hispanic, but only 2% of elementary students enrolled in mainstream GT programming were Hispanic. In the U-46 middle school GT program, only 20% of the students were Hispanic. Similarly, Black students comprised 6.3% of the District student body but only 2% of the GT program in both elementary and middle school. District Judge Gettleman wrote in the courts' opinion:

> Although Dr. Ford testified that, ideally, participation in gifted programs by minorities would roughly equal their proportion of the student population, she recognized that a 20% allowance for cultural differences and voluntary exclusion from gifted programs by minorities was to be expected. Thus, with a population of approximately 40% Hispanic, the District should expect approximately 32% of the children in its mainstream gifted programs to be Hispanic. The fact that only 2% of the children in SWAS [School Within a School—one of the two gifted programs offered by the district; Ford, 2013a] were Hispanic demonstrated to Dr. Ford, and the court, that the District's method to identify gifted Minority Students was flawed and resulted in an obvious disparate impact on those students by separating them from their, gifted White peers. (*McFadden v. Board of Education*, 2013, p. 901)

In District U-46, 20% of the Hispanic student population were native English speakers or had demonstrated English proficiency. The opinion of the court was that even after accounting for the language deficiency argument that U-46 used to defend their separate gifted program for the Hispanic students, English proficient Hispanic students were underrepresented in the mainstream GT program (SWAS). District Judge Gettleman wrote,

> The low numbers and percentages of Hispanic students in the mainstream SWAS gifted program can be viewed from another perspective. The testimony at trial from the District's witnesses . . . revealed that approximately 20% of the Hispanic students spoke fluent English and thus did not require ELL. Taking the 2006-2007 school year as an example, 20% of the 9,476 Hispanic elementary population is 1,895, because approximately 2 to 3% of the White student population were identified as gifted and enrolled in SWAS, one would expect approximately 47 English speaking Hispanic students (2.5% of 1,895) . . . to have been placed in SWAS with sufficient English proficiency to succeed with or without language supports. Even discounting for actual or other minority-based preferences, the fact that only five Hispanic students were in SWAS that year demonstrates that serious flaws existed in identifying gifted Hispanic children, resulting in a serious disparate impact on the Hispanic population. (*McFadden v. Board of Education*, 2013, pp. 900-901)

There are some lessons to be learned from *McFadden*. First, when schools are proactively working to diversify gifted education programs, they should avoid using protected class variables such as race and ethnicity (McBee, Shaunessy, & Matthews, 2012; Peters & Engerrand, 2016). Second, the court found inequitable representation of minority students in gifted education can result in a serious disparate impact on those classes of students. The examination of the 20% equity rule in *McFadden* was somewhat ambiguous. Though Getterman specifically referred to Ford's testimony recognizing the 20% allowance, the court's opinion does not clearly endorse the 20% rule, nor does it dismiss the 20% rule.

Two years after *McFadden*, the U.S. District Court in Arizona revisited the *McFadden* opinion and the 20% rule (*Lohr v. U.S.*, 2015). The Tuscon Unified School District (TUSD) had been under a court ordered desegregation order for several decades. Plaintiffs asserted that minority students were underrepresented in gifted education programs and petitioned the court to include such underrepresentation in the desegregation plan. In the *Lohr* case, TUSD offered in their Unitary Status Plan (USP) a proposal based in part on language used in the *McFadden* decision. The legal meaning of unitary status comes from a 1968 U.S. Supreme Court ruling in *Green v. County School Board*. In desegregation hearings, the courts can determine a school has achieved unitary status when "racial discrimination has been eliminated root and branch" (Moore, 2002, p. 315). Unitary status requires that six specific areas no longer contain "any vestiges of past racial discrimination" (Moore, 2002, p. 315): (a) student assignment, (b) faculty, (c) staff, (d) transportation, (e) extracurricular activities, and (f) facilities. In desegregation legal proceedings, these six areas are commonly known as the *Green* factors. Specifically, TUSD cited *McFadden* in their proposal to the court adhering to the 20% rule as a metric to validate no longer engaging in discriminatory practices in gifted education and advanced learning experiences (ALE). The court approved the original plan using the 20% rule as a guideline for all advanced academic programs (including but not limited to gifted education), but later TUSD petitioned the court requesting flexibility. Specifically, the district requested not adhering to the 20% rule in each of the separate advanced academic programs (gifted education pull-out programs, AP programs, Pre-AP/honors programs, dual credit programs, International Baccalaureate Programs, and dual-language programs).

In the *Lohr* opinion, District Judge Bury rejected TUSD's request for flexibility on the 20% rule in each ALE. Bury's opinion appears to more strongly support the court's use of the 20% rule than *McFadden*, but it is not clear whether school districts should infer the 20% equity allowance as a strict guideline for equitable participation in gifted education or advanced academic programs. Bury wrote,

> As the Court sees it, the problem is that the 20% Rule is an oversimplistic measurement for effectiveness, especially if TUSD intends to apply it to determine unitary status. The Court is not inclined, without full briefing, to consider whether the 20% Rule, establishing a floor, satisfies the USP [Unitary Status Plan] mandate to increase the number of minority students participating in ALEs [Advanced Learning Experiences], which suggests a goal somewhere in the ceiling. (*Lohr v. U.S.*, 2015, p. 3)

In other words, the *Lohr* opinion suggests that the 20% rule is an acceptable guideline that the district might use to evaluate annual goals for equitable participation, but the judge was clear that his opinion should not be read that the 20% rule could satisfy unitary status. Later in the opinion, Bury explained,

> The Court agrees with the District that flexibility is necessary but does not agree with the District that flexibility can be found in the 20% Rule. It is instead an imprecise standard, merely a rule-of-thumb, which may suggest discrimination depending on multiple variables. . . . the Court assumes that 20% Rule will not be the sole basis for determining unitary status. . . . TUSD should provide the Plaintiffs with a 20% Rule Report for each individual ALE [Advanced Learning Experience] program, by grade level. (*Lohr v. U.S.*, 2015, p. 3)

Lohr takes the 20% rule farther as a guideline for equity than *McFadden* did. Judge Bury specifically stated, "IT IS FURTHER ORDERED approving the 20% rule as a rule-of-thumb annual goal to be met as soon as practicable but no later than the USP target date" (*Lohr v. U.S.*, p. 3). It may be inferred from *Lohr*, that the 20% rule is not sufficient for a district to meet unitary status (satisfying court ordered desegregation),

Table 1. Independent Variables Used in Regression Models.

Classification	Variable
Student	Percent Black, Percent Asian, Percent White, Percent Economically Disadvantaged, Percent English Language Learner (ELL)
Teacher	Number of Students per Teacher, Average Years of Experience, Teacher Turnover Rate, Percent With Less Than 5 Years of Experience, Percent With an Advanced Degree, Percent Hispanic, Percent White, Percent Black
Expenditure	Total Instructional Expenditure per Student, Percent of Budget Allocated to Central Administration, Percent of Budget Allocated to GT (Gifted and Talented) Programming, Percent of Budget Allocated to Prekindergarten

but it is also unreasonable that the district could achieve unitary status without meeting or exceeding the 20% equitable allowance for all advanced academic programs, including gifted education. *McFadden* introduced the 20% rule as a potential metric for estimating inequity in gifted education, and *Lohr* more specifically applied it to a school district under a desegregation order.

Consideration of the *McFadden* and *Lohr* court opinions and the increase of litigation in the matters of gifted students (Russo, 2001) warrants the investigation of the 20% equity allowance formula as a potential guideline for measuring and flagging inequitable enrollment in advanced academic programs. Additionally, this study aims to fill a gap in the literature regarding the limited nature of gifted education law previously pointed out by Zirkel (2016). As such, the purpose of this study was to explore inequitable enrollment in GT services through the lens of Ford's (2013b) 20% equity formula, apply the 20% rule to school districts in Texas, and evaluate school district characteristics associated with inequitable enrollment.

This study examined school districts across the state of Texas, because Texas gifted education policies (Texas Education Agency [TEA], 2009) require multiple sources of data to be used for GT qualification, but the school officials make the determination of which data to use and how to weigh each metric in a holistic review. In other words, state policies with more local control allow local education agencies latitude to look beyond standardized test scores with consistent discrepancies across ethnicities when making recommendations for participation in GT programs. Each school district in Texas has significant latitude to develop, implement, and improve gifted identification procedures, and one of the state standards mandates that "access to assessment and, if needed, gifted/talented services is available to all populations in the district" (TEA, 2009, p. 6).

Research Questions

The purpose of the present study is to empirically evaluate the applicability of the 20% rule broadly in the identification of inequitable enrollment in GT programming and, where appropriate, use the rule in an exploration of the factors that may be related to the magnitude of this inequity. Questions guiding this exploratory investigation are

Research Question 1: Can the 20% rule be reasonably applied across all or a subset of races or ethnicities in the state of Texas for the purpose of identifying inequitable enrollment at the district level?
Research Question 2: For the races or ethnicities that the 20% rule can be reasonably applied (as determined in answering Research Question 1), how many districts fail to achieve equity?
Research Question 3: What district characteristics are associated with the magnitude of inequity in GT program enrollment?

Method

Data

Data were taken from three sources: (a) the OCR (2013) data collection 2013 to 2014, (b) TEA (2013) district snapshots, and (c) Common Core of Data (CCD; NCES, 2015) collected in the same year. The OCR collects data on a biennial basis from all public local education agencies and schools in the United States. Within the OCR data set, the number of students by race, ethnicity, and sex who are enrolled in GT programming per school is available. Data taken from TEA provide district-level variables not available from OCR, including percent of teachers of a given race or ethnicity. Finally, CCD provided variables necessary for matching across the TEA and OCR data sets as well as NCES (Geverdt, 2015) district code classification.

Data preparation required several steps. First, charter districts were excluded from TEA. Next, data from TEA and CCD were merged based on state district identification number. This produced a data set with covariates including NCES district classification (1 = *city*, 2 = *suburb*, 3 = *town*, 4 = *rural*). After this, enrollment data from OCR were aggregated to the district level with the exclusion of juvenile justice facilities and inclusion of only schools self-identified as having a GT program. Last, the TEA/CCD data set was merged with the aggregated OCR data set based on local education agency identification number. This resulted in a final data set of 997 districts with district-level variables listed in Table 1. District-level variables were chosen in part because of their malleable nature. For example, in this study,

$$IS = \%ofGT_{Race/Ethnicity} - \overbrace{(District\%_{Race/Ethnicity} - 0.2 * District\%_{Race/Ethnicity})}^{Ford's\ 20\%\ Rule}$$

Figure 1. The inequity score (IS) calculated from Office of Civil Rights enrollment information combined with Ford's (2013a, 2013c) 20% rule.

variables included teacher turnover rate and budget allocation because school districts can adjust class size, allocate some funds differently, improve school climate, and provide professional development to improve areas of concern. Other variables in the study, such as percent English Language Learner (ELL) and percent economically disadvantaged students, were chosen because of the persistence of underrepresentation of ethnically diverse students and students living in poverty (Yaluma & Tyner, 2018) or their relevance as environmental factors (i.e., teacher race/ethnicity) in student identification (Grissom et al., 2017; Yaluma & Tyner, 2018) and student trajectories (VanTassel-Baska & Stambaugh, 2007). A full list of variables included in this study can be found in Table 1. All code for preparing data and running analyses is available online at the Open Science Framework account of the second author.

A value indicating the magnitude of inequity instead of a dichotomous designation was necessary for answering the research questions. The enrollment information from OCR combined with Ford's (2013a, 2013c) 20% rule were used to calculate an inequity score (IS) as given in Figure 1.

Based on this formula, a positive IS indicates a district has surpassed equitable enrollment for a particular race/ethnicity based on the 20% rule. A negative IS indicates that a district has enrolled a lower percent of students of a particular race/ethnicity than would be admissible in applying the 20% rule. For example, if 30% of the students in a district were Hispanic and 10% of students enrolled in the GT program were Hispanic, then

$$\text{IS} = 0.1 - (0.3 - 0.2 * 0.3) = -0.14.$$

The negative IS indicates that the district is underenrolling Hispanic students for the GT program and discriminatory practices may be to blame. IS for each district was calculated because such scores allow for the magnitude of inequity (based on the 20% rule) to be evaluated instead of a simple determination of whether a district is inequitable or not.

Procedures

To answer Research Question 1, the broad applicability of the 20% rule was evaluated. The 20% rule is based on two numbers: (a) the percent enrollment of students of a given race or ethnicity in the district and (b) the percent of students of a given race or ethnicity enrolled in GT programming. Percent values are susceptible to drastic change by the addition or removal of a single case when the overall total is small. In districts in which the number of students of a given race or ethnicity is small, the applicability of the 20% rule is suspect. This is investigated by evaluating the IS values in districts with this population condition with the overall goal of identifying a race or ethnicity to which the 20% rule could be most reasonably applied across the state of Texas.

To answer Research Question 2, inequitable enrollment was then investigated using student race or ethnic groups in which the 20% rule could be reasonably applied across Texas as a result of answering Research Question 1. To meet equity standards for a specific race/ethnicity, the district IS for that race/ethnicity had to be at least zero. The number of districts not achieving equity were recorded.

To answer Research Question 3, multiple linear regressions were conducted with district IS as the dependent variable and the independent variables encompassing district-level characteristics of students, teachers, and expenditures (see Table 1). Regression models were evaluated using complete and subsets of data. Subsetting was based on the four NCES location classifications (1 = *city*, 2 = *suburb*, 3 = *town*, 4 = *rural*) and total enrollment within the rural classification. Total enrollment was limited to a maximum of 2,500 within subsets of rural schools, per the recommendation of Kettler, Puryear, and Mullet (2016). Subsetting allowed the researchers to identify consistency in variable relationships across location classifications without specification of a multitude of interaction terms. The goal was to identify consistent trends and not to test hypotheses of zero difference between groups.

Parameter estimates were calculated using Bayesian estimation. The rationale for using Bayesian estimation is threefold: (a) emphasizes inference in the form of intervals instead of simple point estimates (Gelman et al., 2013), in line with exploratory research where assessing point estimates for statistical significance with p values is not possible, (b) results have more intuitive probabilistic interpretations than more commonly used (frequentist) methods, and (c) Bayesian estimation has great applicability beyond the current analysis (small sample sizes, estimation of complex models), and its increased use could be beneficial to the field. Therefore, the present study has both substantive and methodological implications for the study of gifted education.

Bayesian Estimation

To derive Bayesian estimates, prior information is combined with information from newly collected data to produce updated information indicating which parameter values are most credible. Information is modeled in the form of probability distributions and can be classified as the prior, likelihood, and posterior. A prior distribution for each parameter is mathematically combined with the likelihood through the use of Bayes's theorem to produce a posterior distribution. More formally,

$$p(\theta|D) \propto p(D|\theta)\, p(\theta),$$

where $p(\theta|D)$ is the posterior probability of a parameter estimate being true and is proportional to the product of the likelihood, $p(D|\theta)$, and the prior probability, $p(\theta)$. The prior is a probability distribution that the analyst uses to assign a priori credibility to a range of parameter values. The prior can be specified to assign credibility to parameter values based on estimates from previous studies or to be vague, assigning minimal a priori credibility to a range of values. Assigning vague priors allows the data to primarily determine the posterior. The likelihood is the same distribution maximized to derive maximum likelihood estimates and is based on data only. The combination of these probability distributions is itself a probability distribution, the posterior. In an analysis, each estimated parameter has a posterior distribution describing the credibility of parameter values given the information in the prior and likelihood.

The mean, median, or mode of the posterior can be used as parameter estimates. For a unimodal posterior, the parameter value at the mode has the greatest credibility of being true. The highest density interval (HDI) is the range of values under the posterior distribution that encompasses an area equal to a given percent. The HDI has a probabilistic interpretation: a 95% HDI has a 95% chance of capturing the true value, given the prior and likelihood (Greenland et al., 2016). Such probabilistic interpretations are more intuitive compared to the interpretation of confidence intervals where a 95% confidence interval refers to the proportion of confidence intervals from many replications of a study that would contain the parameter value.

To mathematically calculate a posterior distribution can be impossible, even for seemingly simple problems. With present day computing power, however, the posterior distribution can be approximated by using Markov chain Monte Carlo (MCMC) processes. These procedures construct the posterior distribution by repeated sampling, creating chains of iterations that empirically approximate the posterior. For further description of Bayesian estimation and its use in procedures such as a *t* test (Kruschke, 2013), regression (Kruschke, 2015), or hierarchical linear modeling (Boedeker, 2017), see the cited works.

Bayesian Estimation of IS Regression

In this application, the regression coefficients were not assigned prior distributions but instead Bayesian estimates of correlations were found. From the posterior estimates of correlations, estimates of regression parameters are calculated using the procedures outlined below. The likelihood of the correlation matrix was specified to be multivariate normal with means and covariance matrix. The means and inverse of the covariance matrix were assigned vague prior distributions. Although previous research has been conducted to study inequity, a systematic and justifiable means of incorporating that information into prior distributions of correlations is still to be fully developed in the methodological literature. Each mean of the multivariate normal distribution was assigned a normal distribution prior with mean of zero and variance of four. The prior for the inverse covariance matrix was a Wishart distribution with a $v \times v$ identity matrix as the scale parameter and $v + 1$ degrees of freedom where v is the number of variables (in this case 18, including all predictors and IS). Three MCMC chains were each run for 20,000 iterations with a preceding 5,000 burn-in iterations. All three chains were combined to create posterior distributions. Convergence of the posterior was assessed visually and by the Gelman and Rubin (1992) statistic.

Each iteration of a chain produced a set of correlations between variables in the model. Each of the 60,000 correlation matrices was used to derive standardized regression coefficients by applying the formula

$$\beta = \boldsymbol{R}_x^{-1}\boldsymbol{Y}$$

where β is a vector of standardized weights, $\boldsymbol{R}_x^{-1}$ is the inverse of the correlation matrix of only the independent variables, and $\boldsymbol{Y}$ is a column vector of correlations between each predictor and the dependent variable. Calculating standardized weights using the joint posterior distribution of the correlation matrix makes the distributions of these coefficients posterior distributions as well. Using standardized weights for each predictor and each predictor's bivariate correlation with the dependent variable, the R^2 for each iteration was found using

$$R^2 = \beta_1 r_{x_1 y} + \beta_2 r_{x_2 y} + \cdots + \beta_p r_{x_p y}$$

where p is the number of predictors. The R^2 value indicates the proportion of variability in the dependent variable that can be explained by the predictors as a set. Structure coefficients were derived for each variable in each iteration as well by

$$r_{s,x_p} = \frac{r_{x_p y}}{R}.$$

Squared structure coefficients are the proportion of the total explained variability (R^2) that a single predictor can explain. Structure coefficients are not susceptible to distortion in the presence of multicollinearity, a condition under which standardized regression coefficients cannot provide clear indication of variable importance (Thompson & Borrello, 1985). Following best practice recommendations (Courville & Thompson, 2001; Henson, 2006; Thompson, 1992), both

Table 2. Descriptive Statistics of District Enrollments and IS by Race or Ethnicity.

	Hispanic	Asian	Black	White
Minimum	0	0	0	0
First quartile	83	0	6	165
Median	292	6	25	432
Third quartile	1,242	20	156	1,144
Maximum	131,004	16,116	53,307	31,320
Mean	2,563	185	611	1,490
Standard deviation	8630.8	973.5	2778.9	3369.3
IS minimum	−62.93	−4.57	−26.41	−35.68
IS first quartile	−12.15	−0.26	−2.94	15.33
IS median	−5.32	0	−0.90	24.04
IS third quartile	1.05	2.23	0	32.61
IS maximum	61.16	38.60	46.95	85.07
IS mean	−5.12	1.46	−1.81	24
IS standard deviation	12.75	3.71	4.78	14.05

Note. IS = inequity score. Includes only public schools.

standardized regression coefficients and structure coefficients are reported. Posterior distributions for R^2, standardized regression coefficients, and structure coefficients were derived by the combination of results from the 60,000 regressions. All analyses were conducted in R (R Core Team, 2016) using code developed by Kruschke (2017) and the psych (Revelle, 2017) and rjags packages (Plummer, 2016).

Results

Applicability of the 20% Equity Allowance Formula

See Table 2 for descriptive statistics of enrollment and IS for Hispanic, Asian, Black, and White students. The applicability of the 20% rule was found to be suspect in districts with low enrollments of students of a given race or ethnicity. For instance, one district with two Black students and a total enrollment of 269 had seven students in the GT program. To achieve equity, 0.58% of the GT enrollment would need to be Black students. However, a single Black student in the GT program would comprise 14.3% of the GT enrollment and yield an IS of 13.7. Such a large positive value may indicate overidentification of Black students for the GT program. With zero Black students in the GT program, the IS for the district was −0.58, what would appear to be a small amount of inequity. In cases such as this, using the 20% rule does not adequately identify inequity.

It was determined that the race or ethnicity for which the 20% rule could be most reasonably broadly applied in the state of Texas was Hispanic. Pacific Islander, American Indian, and multiracial were excluded because each comprised less than 2% of the state's enrollment (TEA, 2013), and a majority of districts had zero enrollments of students with these classifications. Whereas there are more Asian and Black students enrolled in public schools in the state of Texas, the number of students within a district was often small. For example, of the 997 districts, 249 had fewer than five Black students and 493 had fewer than five Asian students. For Hispanic students, there were only nine districts with fewer than five Hispanic students, three of which had zero Hispanic students. With a greater distribution of enrollment numbers, the 20% rule was most appropriately applied to identify inequitable enrollment of Hispanic students in GT programming in Texas. Whereas the White population also has a greater distribution of enrollment numbers, inequitable enrollment of this population is less a concern than for Hispanic students. The equity allowance formula could be applied to more narrowed subsets of districts based on limitations of minimum enrollments. Such limitations can be tested and defined in future research. The remaining analyses were limited to Hispanic students only. The three districts with no enrollment of Hispanic students were removed from the data set. This resulted in a total of 994 districts for use in subsequent analyses.

Inequitable Enrollment

To answer Research Question 2, the number of districts flagged for inequitable enrollment of Hispanic students in GT programming was calculated. Of the 994 districts under consideration, 712 (71.6%) did not meet equitable enrollment standards based on the application of the 20% rule. Of the 712 districts flagged for inequity, 41 missed the lower bound of equity by less than 1%.

IS Regression

Bayesian regressions were conducted with district IS for Hispanic students as the dependent variable to answer Research Question 3. Results are presented in Tables 3, 5, and 6 and Bayesian modes are reported for point estimates in text. The correlation matrix of predictors is shown in Table 4. With complete data, the model accounted for modest portions of variability (R^2= .129, 95% HDI [.095, .170]; see Table 3). Large R^2 values were found when subsetting by city, suburban, and town. For instance, for the city districts, the model explained 70.6% of the total variability in IS for Hispanic students with a 95% chance that the true value lies between 58.6% and 78%. The model performed notably less well for rural districts (NCES 4; R^2= .110, 95% HDI [.067, .158]), accounting for only 11% of variability in IS. As such, subsetting by student enrollment size was done within the rural district classification to investigate under which conditions the model ceases to fit. The model when applied to rural districts with total enrollments larger than 800 had fit comparable to town districts, R^2 = .505, 95% HDI [.398, .617]. Given that large portions of variability could be explained by the variables in most models for Hispanic students, further investigation of which variables were meaningful predictors of IS was warranted.

Table 3. R^2 Results: Hispanic Inequity.

	R^2 mean	R^2 mode	95% HDI Lower bound	95% HDI Upper bound	*n*
All	.132	.129	.095	.170	994
NCES 1	.696	.706	.586	.780	73
NCES 2	.747	.753	.669	.824	110
NCES 3	.510	.514	.418	.598	211
NCES 4	.112	.110	.067	.158	553
NCES 1-3	.511	.512	.443	.578	394
NCES 4, 100-2500	.107	.103	.062	.152	540
NCES 4, 200-2500	.152	.149	.096	.210	443
NCES 4, 300-2500	.198	.196	.129	.266	367
NCES 4, 400-2500	.240	.238	.163	.317	312
NCES 4, 500-2500	.254	.250	.170	.340	264
NCES 4, 600-2500	.320	.321	.224	.417	214
NCES 4, 700-2500	.302	.295	.199	.405	176
NCES 4, 800-2500	.507	.505	.398	.617	138
NCES 4, 900-2500	.522	.530	.407	.636	119
NCES 4, 1000-2500	.531	.534	.406	.651	99
NCES 4, 1500-2500	.766	.777	.653	.871	41

Note. HDI = highest density interval; NCES = National Center for Education Statistics; NCES 1 = City; NCES 2 = Suburb; NCES 3 = Town; NCES 4 = Rural; For NCES 4 subcategories, the range of numbers indicates the student enrollment numbers of districts included in the given regression analysis. Posterior mean and mode values are presented. *n* = the number of districts included in the given subgroup analysis. The 95% HDI is interpreted such that there is a 95% probability that the interval contains the true value, given the prior and likelihood.

Across subsets for Hispanic students, percent Hispanic and White teachers were found to be meaningful predictors of Hispanic IS. Table 5 shows standardized regression coefficients and Table 6 the structure coefficients for five models. The percent of Hispanic teachers in a district yielded positive standardized regression coefficients and structure coefficients with HDIs that spanned substantively interesting values across a majority of models. Given the sign of the structure coefficients and standardized regression coefficients, an increased percent of Hispanic teachers was associated with higher IS, indicating a decrease in inequitable enrollment of Hispanic students for GT programming. The percent of White teachers in a district was negatively associated with Hispanic IS as shown by negative standardized regression coefficients and structure coefficients across a majority of models. These negative values of both structure coefficients and standardized regression coefficients reveal that increases in the percent of White teachers is associated with lower IS, which indicates greater inequity in identifying Hispanic students for GT programming. Differences between standardized regression coefficients and structure coefficients for the same predictor can be attributed to multicollinearity (see Table 4).

Additionally, notable results were found for variables in limited subsets of districts. Percent economically disadvantaged had low standardized regression coefficients across subsets but moderate to large structure coefficients for districts coded as city, suburban, or town. Percent ELL was also found to have low standardized regression coefficients but large structure coefficients for larger districts coded as city or suburban. The standardized regression coefficients and structure coefficients for the percent of White students were different from one another within a given model, likely a result of multicollinearity. The percent of White students was also highly correlated with other variables in the model, including percent of teachers who were Hispanic or White. Therefore, the predictive utility of the percent of White students in a district may be attributed to other predictors with regards to standardized regression coefficients.

Discussion

Inequitable access to gifted education has been discussed and debated in the field for decades. Although understanding of the problem has arguably improved, the metric for determining when underrepresentation is or is not occurring remains vague. In other words, how large must the participation gap be before it is considered either problematic, unethical, or unconstitutional? This study was conducted in Texas where state policies and guidelines for identifying and providing programs and services for GT students have existed for more than three decades. Texas policy requires all school districts to identify students to participate in gifted education, and it specifically states that access to gifted education is available to all populations in the district. Guidelines also define recommended and exemplary practices relative to providing

Table 4. Hispanic Students, Full Data Correlation Matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
% Black	1																
% Asian	.134	1															
% White	−.269	−.076	1														
% Eco. dis.	.260	−.268	−.614	1													
% ELL	.082	.074	−.601	.487	1												
Num. of Students per teacher	.164	.250	−.285	−.037	.296	1											
% Teachers with <5 years experience	.203	−.017	−.333	.393	.236	.095	1										
Teacher avg. years of experience	−.157	−.077	.311	−.279	−.303	−.254	−.820	1									
% of Teachers with advanced degree	.166	.301	−.177	−.097	.110	.281	−.059	−.013	1								
Teacher turnover rate	.155	−.133	−.148	.259	−.065	−.186	.419	−.306	−.100	1							
Teacher % Black	.839	.146	−.329	.268	.189	.236	.211	−.197	.219	.128	1						
Teacher % Hispanic	−.163	−.032	−.683	.427	.517	.284	.159	−.203	.110	−.059	−.050	1					
Teacher % White	−.115	−.034	.764	−.490	−.566	−.355	−.227	.269	−.184	.024	−.276	−.937	1				
% of Budget for central admin.	−.147	−.209	.110	.082	−.149	−.555	.057	.032	−.189	.267	−.124	−.077	.120	1			
Total inst. exp. per pupil	−.091	−.109	−.003	.077	−.079	−.682	−.137	.235	−.055	.134	−.103	−.024	.061	.462	1		
% of Budget for GT programs	.054	.190	.001	−.159	.001	.259	−.056	.007	.167	−.109	.068	−.028	−.002	−.188	−.165	1	
% of Budget for pre-K	.140	−.048	−.170	.185	.126	.091	.150	−.115	.115	.011	.117	.074	−.112	.027	−.036	−.048	1

Note. Bivariate correlations are given for the complete data set. Eco. dis. = economically disadvantaged; ELL = English Language Learner; Num. = number; Avg. = average; Admin. = administration; Inst. exp. = instructional expenditures; GT = gifted and talented.

Table 5. Standardized Regression Weights (β s) for Hispanic Inequity, Full Data, NCES Coded City, Suburban, Town, Rural (800-2500).

	Full			City			Suburban			Town			Rural (800-2500)		
		95% HDI			95% HDI			95% HDI			95% HDI			95% HDI	
	β	LB	UB	β	LB	UB	β	LB	UB	β	LB	UB	β	LB	UB
Percent Black	0.097	0.028	0.169	0.033	−0.124	0.204	0.094	−0.058	0.247	0.147	0.019	0.259	0.259	0.109	0.427
Percent White	0.257	0.156	0.357	0.089	−0.291	0.501	0.390	0.041	0.778	0.619	0.410	0.815	0.995	0.775	1.220
Percent Asian	0.011	−0.055	0.077	−0.019	−0.192	0.159	−0.037	−0.179	0.087	−0.023	−0.120	0.082	0.189	0.065	0.321
Percent economically disadvantaged	0.181	0.080	0.261	0.203	−0.132	0.553	0.361	0.099	0.635	0.456	0.315	0.602	0.300	0.100	0.509
Percent ELL	0.017	−0.059	0.095	0.231	0.012	0.428	0.194	−0.003	0.394	−0.117	−0.229	−0.007	0.081	−0.106	0.239
Number of students per teacher	−0.012	−0.072	0.048	−0.102	−0.319	0.115	−0.055	−0.179	0.068	0.144	0.023	0.257	0.061	−0.074	0.192
Percent of teachers with <5 years of experience	−0.019	−0.088	0.046	0.049	−0.112	0.210	−0.098	−0.238	0.047	−0.030	−0.141	0.084	−0.132	−0.289	0.009
Average teacher's years of experience	0.012	−0.049	0.074	−0.008	−0.142	0.134	0.127	0.006	0.246	0.072	−0.032	0.171	0.252	0.104	0.381
Percent of teachers with advanced degrees	0.006	−0.053	0.066	0.067	−0.113	0.234	−0.102	−0.230	0.010	0.013	−0.080	0.118	0.040	−0.070	0.177
Teacher turnover rate	0.083	0.023	0.143	0.046	−0.138	0.238	0.021	−0.093	0.132	0.043	−0.058	0.141	0.040	−0.084	0.162
Teacher percent: Black	−0.019	−0.084	0.054	−0.298	−0.468	−0.142	−0.178	−0.294	−0.051	−0.065	−0.183	0.055	−0.014	−0.161	0.125
Teacher percent: Hispanic	0.176	0.111	0.240	0.285	0.127	0.449	0.216	0.106	0.328	0.131	0.025	0.235	0.048	−0.080	0.184
Teacher percent: White	−0.304	−0.371	−0.234	−0.298	−0.595	0.017	−0.530	−0.744	−0.308	−0.692	−0.850	−0.531	−0.565	−0.739	−0.381
Exp: central admin	0.059	−0.006	0.121	0.037	−0.115	0.203	0.113	0.016	0.230	−0.065	−0.164	0.035	−0.118	−0.247	0.005
Exp: total instructional per student	−0.042	−0.105	0.024	−0.016	−0.234	0.213	0.215	0.078	0.343	0.051	−0.075	0.167	−0.216	−0.360	−0.089
Exp: GT	0.003	−0.061	0.063	−0.083	−0.219	0.056	−0.028	−0.135	0.078	0.020	−0.076	0.129	−0.045	−0.173	0.073
Exp: pre-K	−0.047	−0.104	0.016	0.180	0.031	0.341	−0.111	−0.220	−0.004	−0.070	−0.177	0.029	−0.082	−0.213	0.050

Note. HDI = high density interval; NCES = the National Center for Education Statistics; ELL = English Language Learner; GT = gifted and talented; Exp = expenditures; LB = lower bound; UB = upper bound. Standardized regression weight estimates are the posterior mode. Posterior means and modes deviated from one another only marginally.

Table 6. Structure Coefficients for Hispanic Inequity, Full Data, NCES Coded City, Suburban, Town, Rural (800-2500).

	Full			City			Suburban			Town			Rural (800-2500)		
		95% HDI			95% HDI			95% HDI			95% HDI			95% HDI	
	r_s	LB	UB	r_s	LB	UB	r_s	LB	UB	r_s	LB	UB	r_s	LB	UB
Percent Black	0.224	0.058	0.392	−0.152	−0.394	0.138	−0.043	−0.248	0.179	0.175	−0.007	0.359	0.108	−0.119	0.338
Percent White	−0.257	−0.411	−0.080	−0.727	−0.848	−0.545	−0.652	−0.767	−0.492	−0.388	−0.543	−0.209	0.355	0.133	0.553
Percent Asian	−0.096	−0.257	0.085	−0.368	−0.597	−0.126	−0.455	−0.607	−0.251	−0.151	−0.327	0.042	0.073	−0.159	0.300
Percent economically disadvantaged	0.427	0.267	0.574	0.729	0.546	0.849	0.757	0.631	0.847	0.595	0.441	0.716	−0.020	−0.239	0.221
Percent ELL	0.228	0.059	0.391	0.643	0.434	0.791	0.690	0.552	0.802	0.030	−0.162	0.213	−0.114	−0.337	0.119
Number of students per teacher	0.055	−0.110	0.231	0.188	−0.078	0.445	−0.119	−0.327	0.093	0.284	0.111	0.462	0.109	−0.110	0.347
Percent of teachers with <5 years of experience	0.157	−0.013	0.326	0.030	−0.246	0.293	0.331	0.131	0.515	0.236	0.047	0.407	−0.017	−0.257	0.207
Average teacher's years of experience	0.062	−0.101	0.242	0.101	−0.194	0.343	0.163	−0.049	0.368	0.124	−0.065	0.306	0.163	−0.074	0.381
Percent of teachers with advanced degrees	0.068	−0.100	0.241	0.069	−0.220	0.318	−0.088	−0.302	0.120	0.154	−0.049	0.319	0.107	−0.145	0.316
Teacher turnover rate	0.259	0.090	0.421	0.540	0.306	0.720	0.240	0.023	0.429	0.078	−0.111	0.261	0.054	−0.187	0.275
Teacher percent: Black	0.017	−0.156	0.189	−0.312	−0.532	−0.036	−0.316	−0.509	−0.120	0.004	−0.188	0.189	0.048	−0.179	0.283
Teacher percent: Hispanic	0.348	0.185	0.504	0.566	0.337	0.737	0.562	0.391	0.703	0.313	0.130	0.478	−0.037	−0.258	0.206
Teacher percent: White	−0.675	−0.786	−0.543	−0.723	−0.852	−0.550	−0.723	−0.823	−0.586	−0.721	−0.817	−0.591	−0.194	−0.404	0.047
Exp: central admin	0.077	−0.096	0.246	−0.101	−0.348	0.186	0.042	−0.171	0.257	−0.201	−0.369	−0.003	−0.080	−0.311	0.150
Exp: total instructional per student	−0.055	−0.233	0.108	0.343	0.088	0.573	0.473	0.283	0.629	−0.021	−0.198	0.178	−0.338	−0.534	−0.110
Exp: GT	−0.069	−0.230	0.114	−0.188	−0.425	0.103	−0.390	−0.557	−0.181	−0.058	−0.247	0.126	−0.053	−0.289	0.172
Exp: Pre-K	−0.016	−0.185	0.160	0.423	0.166	0.629	0.123	−0.079	0.340	−0.168	−0.353	0.015	−0.074	−0.301	0.159

Note. HDI = high density interval; NCES = the National Center for Education Statistics; ELL = English Language Learner; GT = gifted and talented; Exp = expenditures; LB = lower bound; UB = upper bound. Structure coefficient estimates are the posterior mode. This value was similar in all cases to the posterior mean. Squaring these indicates the proportion of explained variability that can be attributed to a given predictor.

equitable access to gifted education (TEA, 2009). The exemplary policy guidelines state that, "The population of the total district is reflected in the population of the gifted/talented services program or has been for two of the last three years" (TEA, 2009, p. 12). The recommended standard states that, "Over the past two years, the population of the gifted/talented services program has become more closely reflective of the population of the total district" (TEA, 2009, p. 12).

Even though the Texas policy for gifted education clearly communicates the expectation for equitable access and defines that at the highest level as reflective of the total school population, no specific metrics are mentioned on what is reasonably meant by reflective. Must it be exact, or is there a margin within which one might interpret the gifted population as reflective of the whole? How might a Texas school district evaluate itself annually on the standard of equitable access to gifted education services reflective of the total school population? The data in this study suggested that perhaps in the absence of specific guidelines or answers to those questions, the school districts in Texas are largely not evaluating themselves on this guideline at all. Data indicated that less than 30% of Texas school districts meet the 20% rule for equitable access to gifted education for Hispanic students. Neither the scholarly literature nor the policy in Texas offers a measurement definition of how to estimate *reflects* or *more closely reflects*. Scholars and educators can debate—and certainly they have—whether the 20% rule should be used, but quite honestly, no other alternative has been offered to Texas schools. Anecdotal experiences indicate that when asked whether their gifted/talented population is reflective of the district population, most school leaders admit they do not know. Inequitable access appears to be a problem widely discussed and studied at a macro level, yet largely ignored at the micro level where policy and practice intersect.

Measurement is dictated in some areas of the Texas gifted/talented education guidelines. For instance, the guidelines specify the minimal number of professional development hours required by teachers prior to their assignment to the gifted education program. The guidelines specify the minimum number of data sources to be used in assessment procedures, and they specify the minimum number of members that must participate in the selection committee (TEA, 2009). School districts generally assign a coordinator or director who measures and manages those standards that call for compliance metrics, but as the data herein suggest, school districts may pay less attention to equitable access compliance arguably because there is no metric to determine whether the district meets, exceeds, or falls short of the expectation. As the adage goes, what matters is measured, or better yet, what is measured matters (Bernhardt, 2017).

The *McFadden* and *Lohr* cases have recently sent ripples through equitable access discussions in gifted education and advanced academics. The decision in *Lohr* specifically required the Tucson Unified School District to annually make a report to the court for each advanced academic program, including gifted education, using the 20% rule as the guideline to identify potential areas of inequity. One way to think about these recent cases is that courts and judges do not operate in vagaries when examining the potential violation of civil rights—specifically equal access to gifted education. At a minimum, in a state such as Texas where the state guidelines for gifted education specifically require equitable access, prudence would suggest taking a close look at how the courts measure terms and phrases like reflecting or closely reflecting the total population. Both *McFadden* and *Lohr* involved the underrepresentation of Hispanic students, and Hispanic students comprise 52% of the student population in Texas and 41.4% of the statewide gifted/talented population is Hispanic (TEA, 2017).

Research Question 1 was developed to identify possible limitations associated with the 20% rule to guide subsequent analyses. In both the *McFadden v. Board of Education* (2013) and *Lohr v. U.S.* (2015) cases, student enrollments for both school districts in question were more than 40,000 students with Hispanic students making up the majority population for both districts (OCR, 2013, 2015). When applying the 20% rule to Texas school districts to calculate IS, limitations with the rule were found when trying to assess districts with low enrollments for a given racial/ethnic group, low total enrollment, or low total enrollment in GT programming. The findings in this study did not support the general application of the 20% rule but found that the rule was informative under certain circumstances (i.e., the prevalent Hispanic student population in Texas). The decision to apply the 20% rule, and therefore calculate IS, across Texas for Hispanic students specifically was based on the generally large enrollments in the three areas previously described within districts compared with Asian and Black enrollments in Texas. Districts were further excluded such that any rural designated district with fewer than 800 students were not included in the rural districts model, eliminating 415 districts. Based on the findings in this study, the rule is most effectively applied when a district has a student population greater than 800 and a balanced representation of ethnic groups. These are admittedly rough guidelines and the limits of the applicability of the 20% rule is still an open question, though the work presented here is a step in defining those limits. Considering that two federal court cases, *McFadden* and *Lohr*, have acknowledged the 20% rule as a reasonable metric for identifying inequity in gifted education, more research is warranted to examine the viability of the 20% rule under variable conditions, especially smaller school districts.

Research Question 2 was developed to assess the current state of inequity across Texas school districts. Only 28.4% of school districts met equity standards for Hispanic students. Many studies in gifted education investigate identification and underrepresentation issues suggesting possibilities for increased equity, but fewer studies explicitly define what equitable identification looks like (Gentry et al., 2008).

Therefore, we wanted to move beyond an overall view of inequity in the state of Texas by using the 20% rule to identify school districts and further investigate potential factors related to inequitable gifted enrollment.

In answering Research Question 3, the clearest result of the regression analyses was that the race/ethnicity of teachers was consistently associated with inequitable enrollment. As the percent of White teachers increased, inequity increased. Conversely, as the percent of Hispanic teachers increased, inequity decreased. The relationship between teacher ethnicity (%) and ISs for Hispanic students remained constant across all school types, including rural. In short, teachers matter. This is true not only in a statistical sense but also because of the role that teachers play in the identification of students for GT programming. A student's recommendation to participate in GT programming is dependent on several factors including test results and, oftentimes, teacher referrals/nominations. Given that teacher variables were shown to be associated with inequitable enrollment in GT programming in this study, the teacher referral process was highlighted as a possible mechanism by which inequitable enrollment exists, paralleling similar issues identified in other studies (Frasier et al., 1995; Grissom & Redding, 2016; Grissom et al., 2017; McBee, 2006; McBee, Peters, & Miller, 2016; Olszewski-Kubilius & Thomson, 2010). Typically, teachers' traditional beliefs regarding giftedness center on a student's ability to perform highly on aptitude and achievement tests. This can be problematic when working with ethnically diverse students who may not perform or behave in line with teachers' conceptions of giftedness (Miller, 2009). Additionally, teachers may unknowingly hold stereotypical views and treat ethnically diverse students according to these beliefs. Ford and Grantham (2003) refer to this as deficit thinking, explaining that deficit thinking occurs when educators possess "counterproductive views about culturally diverse students," and thus, respond by "lowering their expectations" (p. 217). At the end of the day, the findings from Research Question 3 highlight what has been supported by other studies: the existence of a relationship between teachers' ethnicity and equitable representation of ethnically diverse students in gifted programming.

The data available in this study did not provide any information on the procedures that schools use to nominate, screen, assess, or place students in gifted education programs. Texas policy places a high value on local control for districts to determine their own process for identifying students for gifted education. Moreover, the state policy has no accountability mechanisms to monitor how districts identify students for gifted education. With 1,029 independent school districts, there are the same number of locally developed policies and procedures for identifying students for participation in gifted education. With no procedural accountability, there is a likelihood that even those locally developed policies for identification are not always followed with precision. The data available revealed a relationship between teacher ethnicity and the equitable enrollment of ethnically diverse students, but again, correlation is not causation, and there could be lurking variables at play. There is no way in this study to pinpoint teacher nominations or any other phenomena as the cause of inequitable enrollment in gifted education but considering why this relationship exists is an area that warrants further qualitative inquiries.

Future Directions

There are multiple issues surrounding inequity in gifted education which this study was not designed to examine. As found within our model, we were unable to perform predictive analyses for Black students using the 20% rule. Investigating underlying variables and their relationship to equity issues for Black students is paramount in advancing gifted education research and practice. Future studies should explore possible predictor variables for Black student inequity as well as investigate what type of districts are modeled well using the 20% rule. This may be accomplished by looking outside the state of Texas and investigating the 20% rule within states with school districts characterized by more diverse populations.

Further research should investigate the district characteristics that support use of the 20% rule. In the *McFadden* and *Lohr* court cases discussed, the rule was utilized within districts that serve more than 40,000 students. Within many Texas districts, the 20% rule was less viable due to district size or student group size. Therefore, other rules or cutoff values within current rules that consider characteristics of districts such as total enrollment should be explored for establishing reasonable equity standards.

Texas policies for identification are locally controlled, meaning the methods in which students are recommended for participation in GT programs and the method in which teacher referrals are conducted is determined by each district administration. Future directions should investigate district protocols for identification using qualitative and mixed methods approaches. This would include detailed descriptions of testing instruments, test cutoff scores, and referral processes. Transparency of such information could provide insight into best practices for equitable identification that could be applied to demographically similar school districts.

Other recommendations suggest that multiple criteria for identification should be used (McBee et al., 2016; Peters & Engerrand, 2016; Siegle et al., 2016; Yaluma & Tyner, 2018) as well as universal screening (Card & Giuliano, 2015; Ford, 2015), and holistic assessments that target potential and high ability (Johnsen, 2011), which also assist with underachievement and misidentification concerns (Olszewski-Kubilius & Thomson, 2010). Replication studies should be performed to further validate the use of multiple criteria and universal screening to increase equitable identification. Also, future studies might evaluate school systems that have deemphasized gifted identification and instead focused in recommendations to participate in GT programs based on demonstrated potential. In other words, school procedures that eliminate paradigms of diagnosis or identification and replace them with paradigms of talent development and potential may yield recommendations to participate based on a broader and more equitable set of metrics. During this analysis, we have identified the school districts in Texas with the best equity index scores. A potential follow-up study that could generate interesting and useful data is a multiple case study design trying to understand the nuances of practice that resulted in those exemplary metrics of equitable access to gifted education.

Additionally, this study employs Bayesian estimation. Bayesian estimation is useful in the study of gifted education because it functions well with small and/or unbalanced samples, requires no correction when making multiple comparisons, and yields results that have intuitive probabilistic interpretations (Kruschke, Aguinis, & Joo, 2012). Though not all of these attributes were exhibited in this paper, they are relevant to the study of gifted education. We encourage other researchers to apply Bayesian methods in their studies of GT students.

Conclusion

Throughout history, it has often been case law that directs our attention to specific issues and concerns in educational policies and practices (Zirkel, 2016). With a history of case law influencing policy, and Texas already mandating equitable access reflective of the total district population, this is more than a theoretical discussion. It is certainly possible that Texas could consider adopting the 20% rule as an equity metric for school districts. Our data suggest that only a small number of schools in Texas would currently meet the equitable enrollment requirements if the 20% allowance rule were the standard. We explored the feasibility of the 20% allowance rule as a widely applied metric. Not surprisingly, the rule does not easily apply in schools with small numbers of students overall or in situations where student groups (race/ethnicity) have small quantities. Arguably, the rule provides an acceptable metric when the population numbers are large enough in a school district.

It is our hope that this study not only adds to the growing awareness of inequity in GT identification, but that the empirical evidence within our study aids districts in identifying practices and procedures within their control that may reduce these inequities and provide opportunity for young people of all backgrounds to reach their potential. In the big picture, we suggest that an accountability policy without a metric is merely a low priority suggestion, and that is certainly a reasonable way to view these data in Texas. To that end, the debate may be less about the efficacy of the 20% rule or whether or not it is supported with valid evidence base and more about whether some metric of inequity is better for kids than no metric at all. At least two Federal District Court cases have suggested that having no metric at all is no longer an option.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Manuscript received**:** 7 September 2017; Final revision received: 10 December 2018; Accepted: 23 January 2019