Article

Journal of Advanced Academics
1–25

DOI: 10.1177/1932202X20969143
journals.sagepub.com/home/joaa
SAGE

Underrepresentation in Gifted Education in the Context of Rurality and Socioeconomic Status

Jaret Hodges[1] and Marcia Gentry[2]

Abstract

Proportional identification of students for gifted services in Florida school districts is an important goal. A multi-level model was used to analyze school district data from the Florida Department of Education from the 2011–2016 academic years. Results from the study indicate that the likelihood of identification of students varied by their socioeconomic status. Students who were Black were 59% more likely to be identified for gifted services if they participated in federal meal subsidy programs. However, the likelihood of identification for students who are Latinx or Native American decreased by 47% and 38%, respectively, when compared with peers who did not participate in federal meal subsidy programs.

Keywords

underrepresentation, multi-level modeling, longitudinal, identification, gifted

Proportional representation of culturally, linguistically, and economically diverse students in gifted programs continues to be a critical issue in the field of gifted education. The idea of proportional representation is a simple one. A school district's identified gifted population should be demographically similar to its general population. However, students who are Black, Latinx, or Native American are currently (Peters et al., 2019) and historically underrepresented in gifted programs (Yoon & Gentry, 2009).

Equitable representation of children in gifted programs and services who are Black, Latinx, or Native American is a critical issue within the field of gifted education

[1]University of North Texas, Denton, USA
[2]Purdue University, West Lafayette, IN, USA

Corresponding Author:
Jaret Hodges, University of North Texas, 1300 W. Highland Street, Denton, TX 76201, USA.
Email: jaret.hodges@unt.edu

(Daniels, 1998; Donovan & Cross, 2002; Erwin & Worrell, 2012; Esquierdo & Arreguín-Anderson, 2012; Ford, 2014; Goings & Ford, 2018; Hodges, McIntosh, & Gentry, 2017; Hodges, Tay, Maeda, & Gentry, 2018; Naglieri & Ford, 2003; Peters et al., 2019; Stambaugh & Ford, 2015; Yoon & Gentry, 2009). Scholars have stated that the causes for underidentification are due to inherent biases in testing (Naglieri & Ford, 2003), cultural bias toward underrepresented groups (Gentry et al., 2014; Grissom & Redding, 2015; Stambaugh & Ford, 2015), lack of educational resources (Hodges, 2018), or issues stemming from academic achievement rather than race/ethnicity (Erwin & Worrell, 2012).

Few studies in gifted education have separated race/ethnicity from other confounding variables such as income status or rurality. McBee (2006) examined the identification of elementary students in Georgia by investigating rates of identification for students of different races/ethnicities while controlling for socioeconomic status (SES) using eligibility for federal meal subsidy as a proxy. Warne et al. (2013) examined identification rates in Utah for students of different ethnicities while controlling for student achievement. Carman and Taylor (2010) controlled for SES using eligibility for federal meal subsidy as a proxy to examine identification rates for gifted services for students identified using the Naglieri Nonverbal Ability Test (NNAT; Naglieri & Ford, 2003). On a national scale, Grissom et al. (2019) examined the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K): 1998 and found that students from high SES households had significant advantages in being identified for gifted services compared with their peers from low SES households within the same school. Using nationally representative data sets to examine access to gifted education can be misleading, though, as state policies regarding gifted education vary greatly across the United States (Peters et al., 2019). In terms of rurality, its interaction with underrepresentation remains a substantial gap in the literature (Rasheed, 2020). This is unsurprising as Rasheed's (2020) literature review of rural gifted education literature pointed out the relative lack of literature on gifted education programs in rural school districts and students identified as gifted in those districts. That said, what is consistently demonstrated within the literature is that rural districts allocate fewer resources to gifted education (Hodges, 2018; Hodges, Tay, Desmet, et al., 2018; Kettler et al., 2016). In contrast, effective identification of students who are traditionally underrepresented requires additional resources and training (Gentry et al., 2014).

The state of Florida allows scholars to explore other explanations for underrepresentation in gifted education programs: SES and locale. Florida mandates that districts report the identification rates of students by federal meal subsidy eligibility. Coupled with district locale classifications, this allows scholars to examine rates of representation for traditionally underrepresented ethnic/racial groups by their federal meal subsidy eligibility, commonly used as a proxy for SES in research (Domina et al., 2018), in the context of their geographic locale. The state requires this of districts as part of their policy referred to as "Plan B" (Florida Department of Education [FDOE], 2017a). Under this policy, the state allows school districts in Florida to develop alternative identification procedures for students who qualify for federal meal subsidies or participate in English Language learning programs.

Underrepresentation in Florida

Identification rates for gifted services for students who are Black, Latinx, or Native American have lagged below students who are Asian or White for decades (Donovan & Cross, 2002; Peters et al., 2019; Yoon & Gentry, 2009). Nationally, based on the 2015–2016 national data from the Office for Civil Rights, students who are Black are represented in gifted programs at a rate of 57% of their current representation in the general K-12 population (Peters et al., 2019). In comparison, students who are Latinx are represented at 70% of the rate of their representation in the general K-12 population. Students who are Native American represented at 87% of the rate of their representation in general population. Using the same data set, Peters et al. found the representation rates for students who are Black, Latinx, or Native American in Florida school districts to be 43%, 88%, and 102%, respectively. This suggests that Florida identifies students who are Latinx or Native American at higher levels than the national average but lower for students who are Black.

In one of Florida's large urban school districts, progress toward proportional representation was made using universal screening (Card & Giuliano, 2016). Scholars provided evidence that the implementation of universal screening between 2004 and 2007 closed gaps in representation between students who are Latinx and students who are White. The implementation of universal screening did not have a similar effect with students who are Black. Regardless, the results from this study highlight the efforts being made within the state to increase equity in urban districts in Florida.

The progress toward proportional identification in the United States is slower among rural school districts (Goings & Ford, 2018). Rural districts often lack the resources necessary to identify and provide services for students from underrepresented populations (Hodges et al., 2019; Hodges, Tay, Desmet, et al., 2018). Critical professional development or faculty hires are postponed indefinitely due to lack of funding (Ihrig et al., 2018). The issue of rurality is critical in Florida as 40% of its school districts are rural.

Florida Rurality

Florida contains some of the densest population centers in the United States (U.S. Census Bureau, 2012). For example, Miami-Dade County has a population of 2,662,874 and 11,135 people per square mile. In contrast, Liberty County, in the Florida Panhandle, has a population of 8,365 and 10 people per square mile. Of Florida's 67 counties, 27 of them are classified as rural (U.S. Census Bureau, 2012). These counties are in two areas in the state. One rural center is within the Florida Panhandle, which is in the northwest portion of the state. The other rural center is located around the Everglades in the central and southern central portion of the state.

Gifted Education in Florida

There are 74 school districts in the Florida. This number is comprised of one school district in each of the 67 counties in the state, the four research universities (Florida

A&M University, Florida Atlantic University, Florida State University, and the University of Florida) each maintain a school district, a school district for children who are blind and/or deaf, a virtual school campus, and a youth detention center (FDOE, 2017a). In total, there are 2,626,008 students enrolled in the Florida public school systems. Of these students, educators identified 165,495 students as gifted and talented representing 6.3% of the state's public school population (FDOE, 2017a).

The state legislators have defined giftedness in children as a child who "has superior intellectual development and is capable of high performance" (FDOE, 2017a). Florida has a dual system for identification. First is an IQ-based identification system in which a child must demonstrate intellectual ability two standard deviations above the mean (IQ = 130). Second is "Plan B" with specific provisions for underrepresented groups within a district. The Plan B identification system is determined by the district. Under Plan B, school districts must have a second identification procedure in place for student groups labeled as underrepresented by the state. The groups recognized by the state as underrepresented groups in gifted education programs, thus qualifying for Plan B, are students learning English as second language and students who participate in federal meal subsidy programs (FDOE, 2017a). Each district must designate identification measures or procedures for identifying underrepresented students for gifted services (FDOE, 2017a).

Purpose

The purpose of this study is to assess how school district-level demographic representation of students who are Black, Latinx, or Native American differs from peers who are Asian or White. A further purpose is to examine how school district locale and participation in federal meal subsidy programs influence this representation. This study addresses a gap in literature regarding the influence of SES, using federal meal subsidies as a proxy, and rurality on representation by examining gifted identification rates among underserved groups in the state of Florida. Furthermore, this study fills a gap between the micro-analysis of a single district by Card and Giuliano (2016), the grade-level analysis from Grissom et al. (2019), and the overall state-level descriptive analysis from Peters et al. (2019).

Research Questions

Research Question 1: To what extent are students who are Black, Latinx, or Native American underrepresented in gifted programs in the state of Florida compared with their peers who are Asian or White?

Research Question 2: To what extent do gifted identification for students who are Black, Latinx, or Native American and participate in federal meal subsidy programs vary when compared with peers who are Asian or White and participate in federal meal subsidy programs?

Research Question 3: To what extent does rurality moderate how race/ethnicity interacts with participation in federal meal subsidy programs and affect identification rates for gifted service?

Method

This analysis used administrative data from Florida and a combination of descriptive statistics and a hierarchical linear model to examine district-level enrollment data. The data used within the analysis are at the school district level. The hierarchical model used in this analysis is a three-level model. For a given year and school district, two rate ratios (RRs) of identification are calculated: one for district enrollment of students in the district who qualify for federal meal subsidies and one for students who do not qualify. These RRs serve as the unit of analysis. As such, the structure of the analysis is the district at Level 3, the repeated annual measure of the school district at Level 2, and the two RRs for a given racial/ethnic group in the school district at Level 1.

Sample

The data set used in this study was acquired from the Accountability and Reporting Department of the FDOE (2017b) using the recommendations of Hodges (2020). Florida annually requires all 74 school districts to report student demographics and testing results to the Accountability and Reporting Department. The FDOE publishes annual aggregate reports for the public and state legislature. This data set was specifically obtained via public access through the PK-20 Education Information Portal (FDOE, 2017b). The data set used in the analysis contains enrollment information for each district's general population and identified gifted population. The enrollment information was disaggregated by race/ethnicity and SES. For example, the data set contained information on the number of students who are Latinx, participate in federal meal subsidy programs, and are identified as gifted for a given year.

The data set used in this analysis encompassed five academic school years (2011–2012 to 2015–2016) and used the variable participation in federal meal subsidy programs, race/ethnicity, gifted education identification, and school district. During the time frame of the study, Florida defined a student as being from a low SES family if they were eligible for free lunch, eligible for reduced-price lunch, or eligible for free meals. In 2017, Florida updated its definition to include all students enrolled in a Provision 2 school or Community Eligibility Provision school (FDOE, 2019). The data analyzed in this study do not include years, wherein the updated definition for participation in federal meal subsidy programs was used. An additional variable designating rurality as denoted by the National Center for Education Statistics (NCLS) was added to the data set. In this study, 27 of Florida's 67 county school districts were classified as rural.

The data set included all school districts in Florida from the academic school years 2011–2012 through 2015–2016 ($n = 74$). Three school districts were eliminated from analysis using listwise deletion because they reported no identified gifted students

during the time frame. Because the dependent variable in this study is a ratio, division by zero yields an undefined result making the observation unsuitable for analysis. The final data set contained 71 school districts over 5 years with 355 observations for all variables. None of the school districts eliminated were rural.

Variables

Description of the dependent variable. Given that rates of identification are being examined, a RR is an appropriate statistic to test in the analysis (Bland & Altman, 2000). A RR is defined as the ratio of the proportion of a group identified as having and not having trait X with the proportion of another group identified as having and not having trait X (Bland & Altman, 2000). RRs are also useful in examining rates of underrepresentation as they directly compare representation between two groups (Hodges, Tay, Maeda, & Gentry, 2018). As the purpose of the study is to examine rates of identification when race/ethnicity and participation in federal meal subsidy programs are controlled, a RR was calculated while conditioning for non-participation in federal meal subsidy programs. In total, six RRs were calculated for each school district for a given year. Two for the demographic count of students who are Black, two for the demographic count of students who are Latinx, and two for the demographic count of students who are Native American using the following formula:

$$\mathrm{RR}_{T,N} = \left(\frac{p\left(\text{gifted} \mid X\ \text{NFRPL}\right)_{T,N}}{p\left(\text{district population} \mid X\ \text{NFRPL}\right)_{T,N}} \right) \div \left(\frac{p\left(\text{gifted} \mid \text{A/W NFRPL}\right)_{T,N}}{p\left(\text{district population} \mid \text{A/W NFRPL}\right)_{T,N}} \right),$$

where T indexes time points and N represents districts. The notation X NFRPL refers to the demographic count of students who are from the racial/ethnic group of interest (Black, Latinx, or Native American) and do not participate in federal meal subsidy programs, and A/W NFRPL refers to the demographic count of students who are Asian or White and do not participate in federal meal subsidy programs.

Finally, a second RR was calculated for students who are designated as having participated in federal meal subsidy programs:

$$\mathrm{RR}_{T,N} = \left(\frac{p\left(\text{gifted} \mid X\ \text{FRPL}\right)_{T,N}}{p\left(\text{district population} \mid X\ \text{FRPL}\right)_{T,N}} \right) \div \left(\frac{p\left(\text{gifted} \mid \text{A/W FRPL}\right)_{T,N}}{p\left(\text{district population} \mid \text{A/W FRPL}\right)_{T,N}} \right),$$

where T indexes time points and N represents districts. The notation X FRPL refers to the demographic count of students who are from the racial/ethnic group of interest (Black, Latinx, or Native American) and do participate in federal meal subsidy

programs, and A/W FRPL refers to the demographic count of students who are Asian or White and do participate in federal meal subsidy programs.

RRs should be interpreted as their magnitude from 1 when discussing representation (Lamb et al., 2019). A RR of 1 equates to equal representation. A RR of 2 equates to the group of interest being twice as represented as the reference group. A RR of 0.5 equates to the group of interest being only half as represented as the reference group.

In the construction of the RRs, the denominator was intentionally chosen to be a composite of the representation of students who are Asian or White. In Peters et al. (2019), these two groups of students are consistently well represented in gifted education programs across the United States. This is in stark contrast to students who are Black, Latinx, or Native American. In short, the purpose of combining students who are Asian and students who are White to form the denominator of the RR is to compare an underrepresented group with a well-represented group.

Predictors. Two predictors were examined for their effect on the dependent variable in the model. The first predictor was SES. The second predictor was rurality. The third predictor, Plan B, was used to perform a check for robustness. Finally, a wave variable was coded that controlled for annual changes across time.

Participation in federal meal subsidy programs (free or reduced-price lunch [FRPL]). A binary variable was constructed to describe RR association with the demographic of students participating in federal meal subsidies. Specifically, this variable indicates whether a RR was calculated using district demographics describing the population of students who are defined as low SES by the state of Florida through participation in federal meal subsidy programs. This variable was coded as 1 or 0 where 1 indicated that the RR was associated with participation in federal meal subsidy programs and 0 indicated that it was not. The indicator for participation in federal meal subsidy programs was associated with RRs that only included students who were designated as participating in federal meal subsidy programs. Using this strategy, RRs calculated from students who do not participate in federal meal subsidy programs would be the reference group in the regression. In this way, the beta coefficient derived from the binary indicator variables is the log mean difference between the RRs describing students who participate in federal meal subsidy programs and the associated RR for students who do not participate in federal meal subsidy programs.

Rurality. A binary variable was created to designate a given RR as being associated with a school district from a rural locale. The rural designation was derived from the codes assigned to the district from the NCES. The NCES (2016) locale designations describe rurality in terms of distance from an urban population center and census designation.

Plan B. A binary variable was created to designate a given RR as being associated with a school district that reported having a Plan B to the FDOE. This variable was used to perform a check for robustness.

Wave. A time variable was created to describe the academic school years. Time was reverse coded such that the academic school year 2011–2012 was coded as −4, 2012–2013 as −3, 2013–2014 as −2, 2014–2015 as −1, and 2015–2016 as 0. Coding time in this manner means that the intercept is indicative of the final time point (2015–2016) rather than the first (2011–2012). Finally, the time variable was allowed to vary across districts as a random effect.

Dependence. The model contained two sources of dependence. The first was that a school district was sampled multiple times. The second is that a set of RRs were calculated from a single school district in a single year.

District. Repeated measures of RRs over time were nested under school districts. This variable was coded as the unique identification number associated with a school district.

Annual District. Repeated measures of RRs were calculated from a single district in a single year. This variable was coded by using the identification number associated with the district cross-referenced with the given year. For example, a given district might be coded as *district1*. For the year 2011, its code would be *district12011*. In this case, two RRs would be assigned this code (one for the RR associated with the demographics of students who participate in federal meal subsidy programs and one for the RR associated with the demographics of students who do not participate in federal meal subsidy programs).

Analysis

As the set of RR used in the analysis was extracted from a school district, these RRs were not independent from each other. In this case, a hierarchical-level model is an appropriate analysis (Faraway, 2014). The data set included repeated measures over time (the RR), which lead to biased estimates if those estimates were not adjusted for lack of independence between observations.

Model Testing

The following model was used in this analysis:

$$\begin{aligned} Y_{ti} &= \alpha + \beta_1\left(\text{low SES status}_i\right) + \beta_2\left(\text{rural}_i\right) + \beta_3\left(\text{wave}_t\right) + \\ &\beta_4\left(\text{FRPL}_i\right)\left(\text{wave}_t\right) + \beta_5\left(\text{rural}_i\right)\left(\text{wave}_t\right) + \\ &\beta_6\left(\text{FRPL}_i\right)\left(\text{rural}_i\right) + \left[u_{00i} + u_{000i} + u_{1i}\left(\text{wave}_{ti}\right)\right] + e_{tij}, \end{aligned}$$

where Y_{ti} is a log RR of identification for school district *i* in year *t* and α indicates the intercept. $\beta_1(\text{FRPL}_i)$ is a binary variable indicating a RR for school district *i* that was calculated from children from low SES households as designated by the FDOE through

participation in federal meal subsidy programs (FRPL). The variable $\beta_2(\text{rural}_i)$ is a binary variable indicating if school district *i* is in a rural designated county. $\beta_3(\text{wave}_t)$ is the time variable. Three interactions are included in the model: $\beta_4(\text{FRPL}_i)(\text{wave}_t)$, $\beta_5(\text{rural}_i)(\text{wave}_t)$, and $\beta_6(\text{FRPL}_i)(\text{rural}_i)$. These represent the interaction between FRPL status indicator and time, district rurality and time, and finally, FRPL status indicator and district rurality. u_{00i} represents the random intercept school district *i* and u_{000i} represents the random slope for repeated measures of RRs within school district *i* in year *t*. Furthermore, $u_{1i}(\text{wave}_{ti})$ represents the random effect of the time variable on slope. Finally, due to a reduced number of degrees of freedom for sub-analyses for students who are Black, Latinx, or Native American, the random intercept for school district and random slope for *wave* were uncorrelated. The model that included a correlated slope and intercept led to convergence issues due to limited degrees of freedom and was uninterpretable.

A Wald *t* test was used as the test statistic in the analysis as suggested by Faraway (2014). As the regression model incorporates fixed and random effects, a more parametric test statistic is inappropriate (Faraway, 2014). R 3.4 (R Core Team, 2017), in conjunction with the *lme4* package (Bates et al., 2014) and the *lmerTest* package (Kuznetsova et al., 2017), was used for the analysis.

In *lme4*, degrees of freedom for statistical tests are calculated with a Satterthwaite adjustment (Bates et al., 2014). Finally, Xu (2003) noted that using traditional effect size calculations for multi-level models (MLMs) can lead to over-optimistic effect sizes. The author suggested the use of a modified coefficient of determination called Ω^2 (Xu, 2003). This coefficient of determination was used in all effect size calculations reported in the analysis.

Weighting procedure. A non-linear probability weighting scheme was used as suggested by Dupraz (2013). When using analytical weights, each school district is weighted by the total number of students in that district in a given year. For example, in 2011, Charlotte County had 17,838 students enrolled. In contrast, Glade County School District had 1,490 students enrolled. The weight associated with the RR for Charlotte County School District in 2011 would be roughly 12 times greater than for Glade County School District. This weighting strategy has the advantage of producing accurate regression estimates reflective of parameters across the state. As the purpose of this analysis is to extract parameters reflective of Florida, this is an appropriate weighting strategy. For race/ethnicity-specific dependent variables, a weight was calculated based on the total number of students of a given race/ethnicity in that district in a given year.

Assumptions. Linear regression assumes a linear relationship between the predictors and outcome, equal variance of errors, and independence of residuals, and that the fixed and random residuals are normally distributed (Seber & Lee, 2012). The use of a RR as a response variable leads to a violation of normality. In this case, Faraway (2014) suggested using a log transformation to address issues of normality.

Furthermore, because the model incorporates repeated measures (multiple years), independence of residuals was violated. As such, an MLM must be used (Faraway, 2014). Finally, the assumption of constant variance of fixed and random effects was addressed by analyzing residual plots.

Robustness. A test for robustness involves examining the change in magnitude and direction of effects of interests through the inclusion of differing covariates or a respecification of a variable (Bradley, 1978). In the case of this analysis, one critical test for robustness is included. Florida does not mandate that districts create a Plan B for identification. Previously, scholars have found that Plan B increases the identification rate of students from underrepresented populations (Matthews, 2007; Matthews & Shaunessy, 2010; McBee et al., 2012). During the time frame of this study, 42 districts reported having a Plan B. For this test of robustness, a binary variable was created that signifies that a district has a Plan B. This variable was then included within the model to examine how controlling for the presence of a Plan B within a district influenced the magnitude and direction of FRPL.

P Values. The p values are reported in these analyses. Considering that this is largely an observational study on the population of Florida districts in the time frame, the reported values should not be interpreted as inferential claims (Makel & Plucker, 2017). The p value is derived from the Wald t test. The Wald t test is calculated from the ratio of the beta coefficient to its associated standard error. Given this, the p value is indicative of a coefficient stability, where low p values are associated with stable beta coefficients. In this case, stable beta coefficients are associated with beta coefficients with smaller standard errors such that the ratio of the beta coefficient to the standard error is greater than 2 (Faraway, 2014).

Results

An important consideration in the interpretation of these results is that they were derived from school district reported enrollments rather than individual students. More specifically, the results of the regression analysis describe demographic representations in identified populations of gifted students associated with school districts in Florida. Any reference to students is in reference to the population of that group of students within a school district in Florida.

Demographics

During the period of this study, total enrollment increased from 2,443,674 to 2,533,505. Enrollment for students who are Asian increased from 59,443 to 63,488. Enrollment for students who are Black increased from 598,457 to 612,813. Enrollment for students who are Latinx increased from 724,312 to 834,189. Enrollment for students who are Native American decreased from 9,336 to 8,521. Finally, enrollment for students who are White decreased from 1,052,126 to 1,011,494 (see Figure 1).

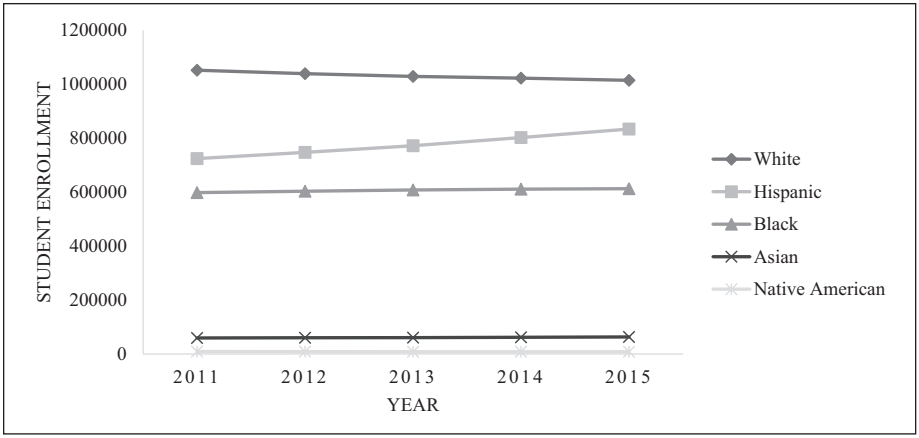

Figure 1. Enrollment by race in Florida public schools from the 2011–2012 to 2015–2016 academic school years.

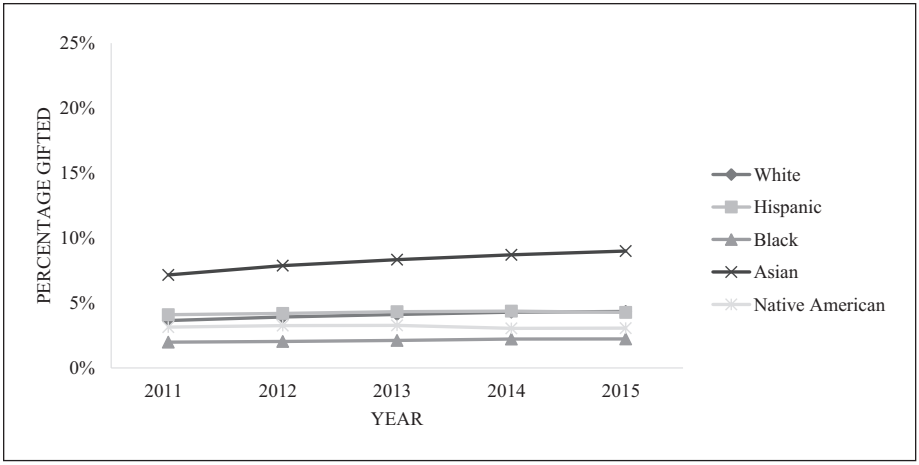

Figure 2. Identification rates by race for gifted services for students from low SES households in Florida public schools from the 2011–2012 to 2015–2016 academic school years.
Note. SES = socioeconomic status.

During the time frame of the study, the percentage of students identified for gifted services averaged 5.71% or 150,365 students. Students who participate in federal meal subsidy programs were identified at lower rates than students who do not participate in federal meal subsidy programs. The percentage of students identified as gifted increased for all demographic groups with exception of students who are Native American and participate in federal meal subsidy programs (see Figures 2 and 3).

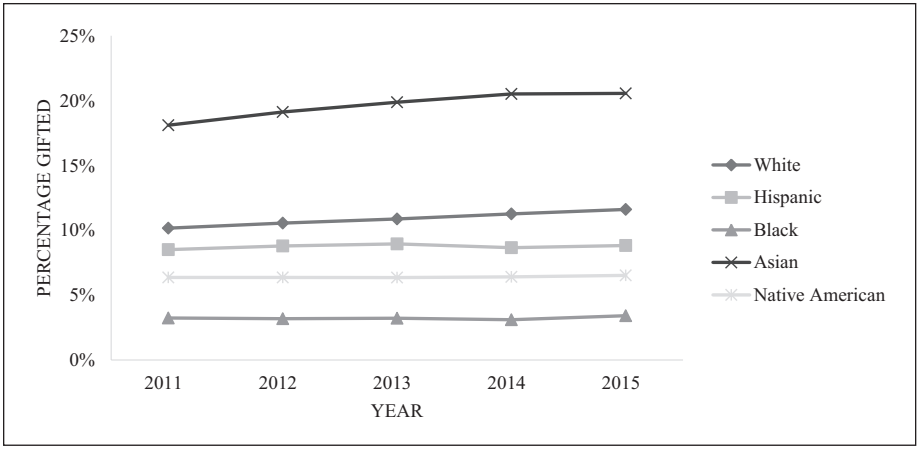

Figure 3. Identification rates by race for gifted services for students from non-low SES households in Florida public schools from the 2011–2012 to 2015–2016 academic school years.
Note. SES = socioeconomic status.

Students who are Black in the state of Florida are only identified at about a quarter the rate of students who are Asian or White (RR = 0.277). The RR identification rates for students who are Black decreased from 0.284 to 0.276 between 2011 and 2016. The RR identification rates for students who are Latinx decreased during this period, falling from 0.672 to 0.617. Students who are Latinx (RR = 0.645) were identified at nearly two thirds the rate compared with students who are Asian and White. Finally, students who are Native American were being identified at a rate of 0.529. This is only over half the rate of identification for their peers who are Asian or White. Identification rates for students who are Native American also declined from 0.564 to 0.498. Between the 2011–2012 school year and 2015–2016 school year, the overall Black and Latinx student populations increased, while the Native American student populations declined. For full descriptive statistics, see Table 1. The distribution of rate ratios across school districts by SES status for students who are Black, Latinx, or Native American can be seen in Figures 4, 5, and 6 respectively.

Model Diagnostics and Fit

Residual plots provided evidence that constant variance was maintained for fixed and random effects. An examination of the QQ-plot provided evidence that a transformation was necessary. Normality was achieved after a log transformation of the dependent variable.

Regression Results

The reported beta coefficients have been exponentiated to provide clear interpretations of effects. In a model that analyzes RRs, a one-unit increase in a coefficient correlates

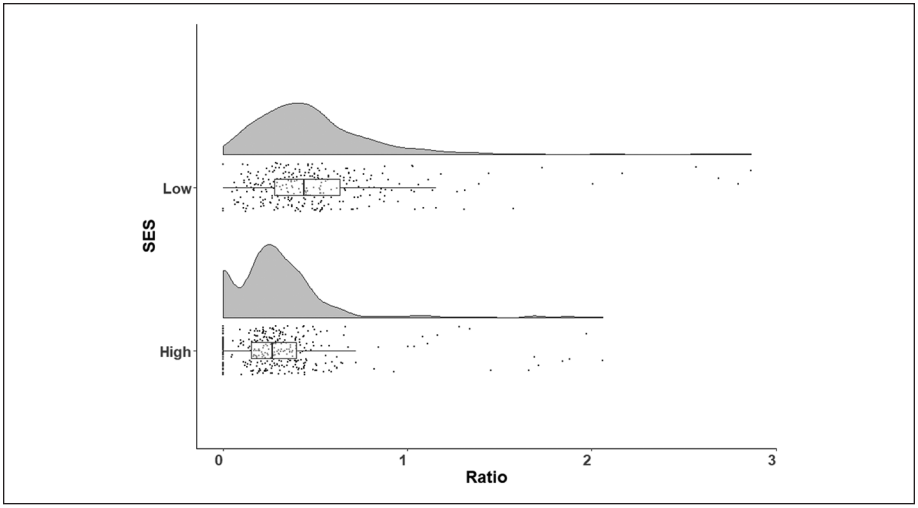

Figure 4. Raincloud plot depicting the distribution and centrality of RR of identification for students who are Black in comparison of students who are Asian or White in Florida.
Note. SES = socioeconomic status; RR = rate ratio.

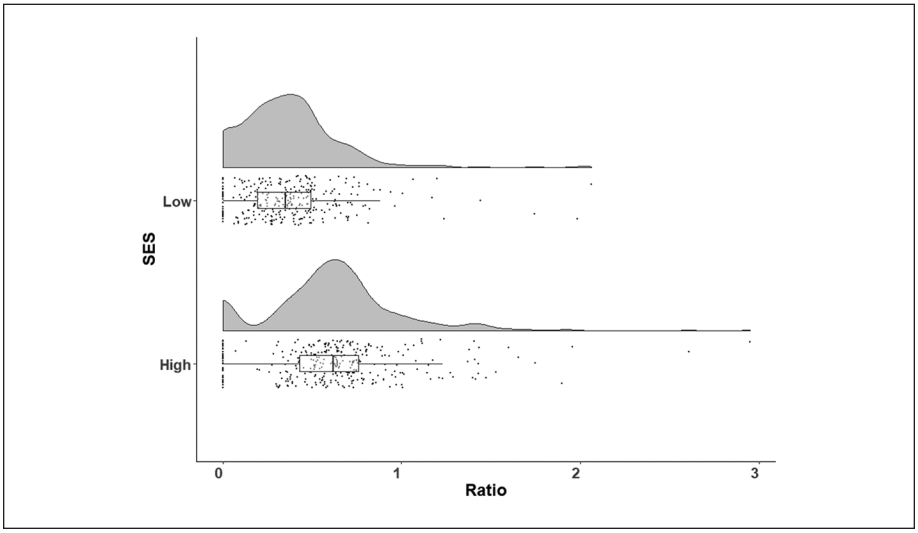

Figure 5. Raincloud plot depicting the distribution and centrality of RR of identification for students who are Latinx in comparison of students who are Asian or White in Florida.
Note. SES = socioeconomic status; RR = rate ratio.

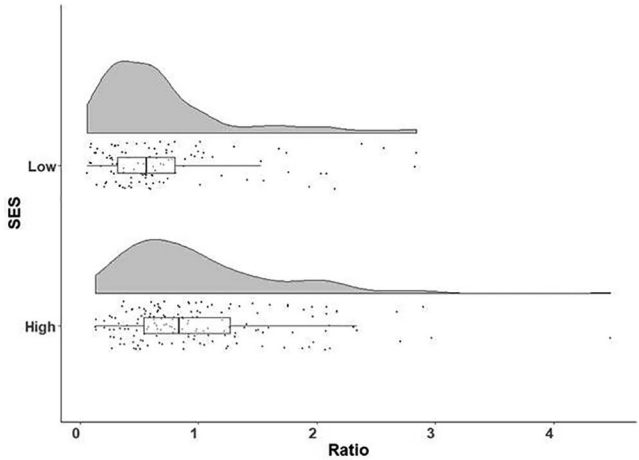

Figure 6. Raincloud plot depicting the distribution and centrality of RR of identification for students who are Native American in comparison of students who are Asian or White in Florida.
Note. SES = socioeconomic status; RR = rate ratio.

Table 1. Descriptive Statistics About Florida's Student Population of Students From Underserved Racial Groups From 2011 to 2016.

Student group	School year	*n*[a]	RR[b]
Black	2011–2012	611,929	0.284
	2012–2013	617,467	0.276
	2013–2014	625,567	0.274
	2014–2015	625,769	0.275
	2015–2016	628,066	0.276
Latinx	2011–2012	762,840	0.672
	2012–2013	788,084	0.656
	2013–2014	815,239	0.650
	2014–2015	847,423	0.633
	2015–2016	880,634	0.617
Native American	2011–2012	9,753	0.564
	2012–2013	9,315	0.548
	2013–2014	8,980	0.532
	2014–2015	8,830	0.506
	2015–2016	8,904	0.498

Note. The RR compares the given student group with the rate of identification of students who are Asian or White.
[a]*n* is the total number of students in the race/ethnic group within Florida's public school system. [b] RR is the rate ratio of identification for gifted services.

Table 2. Regression Results For Students Who Are Black Rather Than Black Students.

Fixed effects	Exp(β)	*SE*	*t*	*p*
Intercept	0.286	0.086	14.550	<.001
Low SES	1.593	0.086	5.414	<.001
Year	1.000	0.023	0.015	.988
Rural	1.139	0.126	1.031	.302
Low SES × Year	1.022	0.032	0.688	.491
Year × Rural	1.014	0.033	0.423	.672
Low SES × Rural	0.549	0.091	6.610	<.001
Random effects	**Variance**	***SD***		
District	0.085	0.292		
Year	<0.001	0.001		
Residual	0.008	0.091		

Note. SES = socioeconomic status.

to an increase in the log RRs (Faraway, 2014). For this reason, the coefficients reported have all been transformed and were written as exp(β) to remind readers of the transformation. The transformation was done for ease of interpretation by the reader. This transforms the scale from log RRs to RRs.

Students who are Black. Rates of proportional identification for students who are Black and participate in federal meal subsidy programs were 59%, exp(β) = 1.594, $p < .001$, greater compared with their peers who are Black and do not participate in federal meal subsidy programs. This means that the RR for identification of students who are Black is 59% greater than the RR of 0.286 for students who are Black and do not participate in federal meal subsidy programs when compared with students who are Asian or White and do not participate in federal meal subsidy programs. This translates into a RR of 0.456. Students who are Black and do not participate in federal meal subsidy programs in rural areas were not identified differently than their non-rural peers overall, exp(β) = 1.139, $p = .302$. This was not the case for students who are Black and participate in federal meal subsidy programs in rural areas, exp(β) = 0.549, $p < .001$. Proportion of variance explained by the model was 28.99%. Full results can be seen in Table 2.

Students who are Latinx. In contrast to students who are Black, the rates of proportional identification for students who are Latinx and participate in federal meal subsidy programs decreased by 47%, exp(β) = 0.532, $p < .001$, when compared with their peers who do not participate in federal meal subsidy programs. Similar to students who are Black, there was a nominal change in identification rates for students who are Latinx and do not participate in federal meal subsidy programs in rural school districts when compared with their non-rural peers, exp(β) = 1.122, $p = .300$. Furthermore, this

Table 3. Students Who Are Latinx Rather Than Latinx Students.

Fixed effects	Exp(β)	*SE*	*t*	*p*
Intercept	0.655	0.076	5.547	<.001
Low SES	0.532	0.077	8.252	<.001
Year	0.956	0.023	1.957	.050
Rural	1.122	0.111	1.037	.300
Low SES × Year	1.100	0.028	3.384	<.001
Year × Rural	1.003	0.029	0.092	.927
Low SES × Rural	0.817	0.082	2.475	.013
Random effects	**Variance**	***SD***		
District	0.067	0.260		
Year	<0.001	0.001		
Residual	0.007	0.081		

Note. SES = socioeconomic status.

coefficient is unstable indicating large variance among districts in the state. Conversely, a time interaction was large and further stable. The rates of proportional identification for students who are Latinx and participate in federal meal subsidy programs increased by 10% each year during the period of the analysis, exp(β) = 1.100, $p <$ .001. Proportion of variance explained by the model was 43.12%. Full results are contained in Table 3.

Students who are Native American. The rates of proportional identification for students who are Native American and participate in federal meal subsidies decreased by 38%, exp(β) = 0.624, $p <$ .001, when compared with their peers who do not participate in federal meal subsidies. Similar to the other demographic groups, there was a nominal change (and with instability suggested by the variance component) in identification rates for students who are Native American who do not participate in federal meal subsidies in rural school districts when compared with their non-rural peers, exp(β) = 1.212, p = .504. The difference between students who are Native American who participate in federal meal subsidies in rural school districts and their peers from non-rural school districts was minimal and unstable suggesting that a practical difference does not exist, exp(β) = 1.151, p = .821. Proportion of variance explained by the model was 21.01%. Full results are shown in Table 4.

Robustness. Results from the test for robustness can be seen in Table 5. The results from this test provide evidence that the inclusion of Plan B within a school district does not influence the direction or magnitude of the effect of rurality or participation in federal meal subsidies on rates of representation.

Table 4. Students Who Are Native American Rather Than Native American Students.

Fixed effects	Exp(β)	*SE*	*t*	*p*
Intercept	0.778	0.110	2.290	.022
Low SES	0.624	0.130	3.616	<.001
Year	0.978	0.037	0.610	.542
Rural	1.212	0.288	0.668	.504
Low SES × Year	1.065	0.053	1.186	.236
Year × Rural	1.204	0.094	1.969	.049
Low SES × Rural	1.151	0.622	0.226	.821
Random effects	Variance	*SD*		
District	0.084	0.290		
Year	0.001	0.025		
Residual	0.012	0.112		

Note. SES = socioeconomic status.

Table 5. Robustness Check of Model Coefficients.

Fixed effects	Black	Latinx	Native American
Intercept	0.219	0.636	0.528
Low SES	1.591	0.532	0.622
Year	1.001	0.956	0.977
Rural	1.281	1.142	1.390
Low SES × Year	1.023	1.100	1.066
Year × Rural	1.012	1.003	1.185
Low SES × Rural	0.549	0.817	1.458
Plan B	1.367	1.036	1.546

Note. SES = socioeconomic status.

Discussion

To What Extent Are Students Who Are Black, Latinx, or Native American Underrepresented in Gifted Programs in the State of Florida in Comparison With Their Peers Who Are Asian or White Between the Years 2011 and 2016?

The overall rate of identification for the combined underrepresented populations is only half of that compared with their peers who are Asian or White. This coincides with the results of numerous researchers who have noted similar trends across the United States (Esquierdo & Arreguín-Anderson, 2012; Konstantopoulos et al., 2001; Peters et al., 2019; Stambaugh & Ford, 2015; Yoon & Gentry, 2009).

As reported by Yoon and Gentry (2009) and Peters et al. (2019), Florida is no exception to the national trends concerning underrepresentation of students who are Black, Latinx, or Native American for gifted services in K-12 public schools. The authors noted that children who are Black or Latinx were identified at a lower rate than their peers who are Asian or White, whereas Native Americans were proportionately identified in the state of Florida. Yoon and Gentry and Peters et al. used a representation index (proportion of students of a given race/ethnicity in the gifted program over the proportion of students in the general population) to quantify representation in gifted programs. Peters et al. reported representation indices for students who are Black, Latinx, or Native American in Florida using the 2015–2016 Office of Civil Rights mandatory reported data of 0.43, 0.88, and 1.02, respectively.

However, the findings for the rate of identification for students who are Native American in this study did not align with the findings of Yoon and Gentry (2009) nor those of Peters et al. (2019). In Florida, students who are Native American were identified at a lower rate than what the Office for Civil Rights data indicated in both studies. Yoon and Gentry (2009) indicated a representation index for Native American students of nearly 1. This index is higher than the one reported in this study (0.529). The results from this article provide evidence that students who are Native American were only identified at half the rate of students who are Asian or White. Native Americans are the smallest of the three populations analyzed (students who are Black, Latinx, or Native American). A possible cause for the differences between estimations of representation reported by Yoon and Gentry (2009) and Peters et al. (2019) when using the Office for Civil Rights data and this study that used data from the FDOE is the estimation procedures on a small population. The Office for Civil Rights data use a minimum cell value of 2 in its reporting. For students who are Native American who only comprise 0.3% of the state's student body, this can lead to overestimates of their representation in gifted programs in the state.

Compared with the national averages presented by Konstantopoulos et al. (2001), Florida has improved rates of identification for students who are Latinx and improved rates of identification for children who are Native American and do not participate in federal meal subsidies. Similar to the findings by Yoon and Gentry (2009), Florida has a lower rate of identification for students who are Black. Konstantopoulos et al. found an overall rate of representation for students who are Black to be 0.37 and Peters et al. reported a rate of 0.43. A ratio of identification of only 0.277 confirms that Florida educators continue to struggle to identify students who are Black despite the legislative mandates and provisions issued by the state.

To What Extent Are Gifted Identification Rates Influenced by Race/Ethnicity When Conditioning for Participation in Federal Meal Subsidies (Through Plan B) in the State of Florida From the 2011–2012 Through the 2015–2016 Academic Years?

The results from this study provide evidence that the interaction between race/ethnicity and SES is not uniform across students who are Black, Latinx, or Native American.

Furthermore, the results of this study are in contrast to those of Erwin and Worrell (2012) and Warne et al. (2013). In both studies, the authors controlled for achievement while examining the effect of ethnicity was not significant a determinant in identification for gifted services. Both groups of researchers found that race/ethnicity was not a significant predictor when achievement was controlled for. However, the data from Florida revealed that when conditioning on participation in federal meal subsidies, the representation gap between children who are Black, Latinx, or Native American and their peers who are Asian or White was not eliminated. In other words, based on Erwin and Worrell's (2012) and Warne et al.'s (2013) studies, if a child who is Black, Latinx, or Native American and a child who is Asian or White achieve on similar levels, they are equally likely to be identified for gifted services. However, this study provides evidence that if a child who is Black, Latinx, or Native American participates in federal meal subsidies, the rate of identification for gifted services is lower when compared with a child who is Asian or White from a similar economic background. In practical terms, Florida's Plan B did not eliminate the gap in identification.

Stambaugh and Ford (2015) and Esquierdo and Arreguín-Anderson (2012) noted that race/ethnicity was still consequential in determining whether a child would be identified for gifted services. Even when participation in federal meal subsidies was conditioned on, and despite seeing some increase in identification rates, students who are Black were still more underrepresented compared with all other racial/ethnic groups within the state of Florida. When conditioning on participation in federal meal subsidies, students who are Black and participate in federal meal subsidies are only identified at 45% of the rate of their peers who are Asian or White and participate in federal meal subsidies. Also, students who are Black and do not participate in federal meal subsidies are identified at only 29% of the rate of their peers who are Asian or White and do not participate in federal meal subsidies. In other words, students who are Black, regardless of their participation in federal meal subsidies, are identified at lower rates compared with their peers who are Asian or White.

Of all student populations, students who are Latinx who do not participate in federal meal subsidy programs are most favorably identified (0.66) when compared with their similar economic status peers who are Asian or White. However, students who are Latinx who participate in federal meal subsidy programs are identified at a much lower rate than their peers who do not participate in federal meal subsidy programs (0.35). This finding corroborates Esquierdo and Arreguín-Anderson (2012) who advised caution to states with large populations of students who are Latinx and issues of underidentification. Despite a rate of identification equal to nearly 0.62 during the 5-year time frame in comparison with that of students who are Asian or White, when conditioning on SES, the rate of identification for students who are Latinx and participate in federal meal subsidy programs falls to nearly 0.35. In comparison, the likelihood of proportional identification increased by 10% per year for students who are Latinx and participate in federal meal subsidy programs. A 10% increase on a RR of .35 equates to a nearly 20-year time frame to achieve proportional rates of identification.

In the case of students who are Native American, the effect of race/ethnicity when conditioning on participation in federal meal subsidy programs is disconcerting. Although the identification rates were still greater than what Konstantopoulos et al. (2001) reported, it is alarming to note that conditioning for participation in federal meal subsidy programs only shows the disparity in likelihood of identification for students who are Latinx or Native American who participate in federal meal subsidy programs. In other words, when you condition on SES for these students, their likelihood of identification is lower. This finding aligns with the observations of Gentry et al. (2014) with regard to students who are Native American. The authors in that study found the factors of race/ethnicity and culture influenced how these students interacted with gifted programs, even when poverty and rurality were considered.

To What Extent Does Rurality Moderate How Race/Ethnicity Interacts With SES in Terms of Identification Rates for Gifted Services Between the Academic Years 2011–2012 and 2015–2016?

The addition of the variable describing participation in federal meal subsidies provided more clarity to the relationship between rurality and race/ethnicity. The results of this study indicate that the relationship between the rurality and race/ethnicity is nuanced. In the case of students who are Black, the effect of rurality and participation in federal meal subsidies is more complicated. For students who are Black living in rural areas, participation in federal meal subsidy programs did not have a uniform effect. For students who are Black and do not participate in federal meal subsidy programs, identification rates did not differ between students from rural and non-rural locales, whereas students who are Black and participate in federal meal subsidy programs were identified at lower rates in rural settings. In other words, if you are a student who is Black and participate in federal meal subsidies in a rural school district, then you are less likely to be identified as gifted than a student who is Black and participates in federal meal subsidies not from a rural school district, $\exp(\beta) = 0.549$.

Like students who are Black, students who are Latinx and do not participate in federal meal subsidy programs have an increased likelihood of being identified for gifted services in rural schools. Because students who are Latinx were identified at higher rates than students who are Black, even though their likelihood of identification increased by the same amount, participation in federal meal subsidies has a bigger effect on students who are Latinx than for students who are Black. In other words, a 27% increase from a RR of 0.67 for students who are Latinx is a greater increase for a RR of 0.22 for students who are Black.

For students who are Native American, there was no effect of rurality in conjunction with participation in federal meal subsidy programs on their likelihood of identification for gifted services. This provides evidence that, for students who are Native American, the overall causes of underrepresentation are independent from rurality. Montgomery (2001) observed that the causes for underrepresentation were due to cultural misunderstanding and lack of awareness. The results from this study did not provide evidence to support the Montgomery (2001) observation, but they can at least

extend the findings by providing evidence that rurality is not related to underrepresentation of students who are Native American in gifted education programs.

Although the main effect results of rurality extend the findings of Kettler et al. (2016), when participation in federal meal subsidy programs was controlled for, race/ethnicity becomes a significant factor in how rural gifted programs are structured. This interaction between locale, race/ethnicity, and participation in federal meal subsidy programs represents a new finding in the field of gifted education. Furthermore, the intersection between locale, race/ethnicity, and participation in federal meal subsidy programs does not have a uniform effect across all three racial/ethnic groups. Although all three racial/ethnic groups are underrepresented in rural communities, the effect of SES for students who are Native American is different from students who are Black or Latinx. The results demonstrate the nuanced interaction of rurality, SES, and race/ethnicity (all considered factors contributing to the excellence gap by Plucker et al., 2010).

Limitations

This study is limited to data from Florida. This makes drawing inference for other states inappropriate, but it does provide a model and method that others can use to examine similar data. The identification rates of underrepresented populations presented by Yoon and Gentry (2009), Peters et al. (2019), and Konstantopoulos et al. (2001) differed from the findings in this study. These differences may be due to the distinct makeup of the population of Florida and the laws and policies associated with gifted programming in the state, different time frames examined, and inconsistencies between different data sets used.

Another limitation involves unknown district-level identification policies. Florida mandates a two-plan structure for identification, but districts have some level of autonomy in enacting this mandate. This is especially true for "Plan B" identification procedures. It is possible a portion of the error variance can be explained by the differences in identification procedures used for "Plan B" across districts.

Furthermore, although this study reported the RR and controlled for covariance between school and years, there is likely covariance that still exists within the data, which is impossible to control for given the nature of the data set. The data set lacked student-level data and was only aggregated at the school district level. Thus, true independence of observations is impossible to obtain. As such, inference must be limited or at least approached with caution. It is likely, though, that the results of this study would not greatly change if student-level data were incorporated into the formulation of the RRs. In part, the use of an MLM accounted for this lack of independence.

As well, the time frame that this study assesses is limited. Florida implemented Plan B in 1991. There is the possibility that a larger time frame examination would yield differing results. That said, this study is focused more so on the ability to examine representation of racial/ethnic groups with similar SES rather than a whole examination of the efficacy of Plan B.

Finally, there is another issue stemming from data not being at the student level. There is the possibility that the lack of student-level data could create unaccountable

error in the results. For example, a child who is Black identified as gifted moves from a rural district to a large district (e.g., Miami-Dade). Given the likely fewer students who are Black in rural districts, and the nature of the RR, that student's exit from the district can have a large effect on the RR calculation for the rural district. Conversely, the entrance of the student to the large district would have little effect on the RR. This limitation is partially addressed through the use of weighting.

A final limitation is in the nature of the RR. In particular, RRs are sensitive to small sample sizes (Bland & Altman, 2000). For example, in a district with only 10 students who are Black, an increase of identification of a single student has a much larger effect on the overall ratio than if the district had 1,000 students who are Black. Rural districts, with smaller student populations, are especially susceptible to this statistical phenomenon. As such, the coefficients derived from rural districts should be interpreted with an additional level of caution.

Conclusion

The results from this study demonstrate that race/ethnicity still matters. Furthermore, results demonstrate that the effects of race/ethnicity are in some cases (students who are Native American) magnified when participation in federal meal subsidy programs. This demonstrates that the construct of race/ethnicity does not behave uniformly with regard to and participation in federal meal subsidy programs, commonly used as a proxy for SES (e.g., Florida).

Even though students who are Black, Latinx, or Native American are often clustered together under the label of underrepresented populations, each group is culturally different from the other. It should then come as no surprise that participation in federal meal subsidy programs does not have a uniform effect across all three underrepresented student populations.

Declaration of Conflicting Interests

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

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Jaret Hodges https://orcid.org/0000-0002-4427-5247

References

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2014). *lme4: Linear mixed-effects models using Eigen and S4* (R Package Version 1.1-23). https://cran.r-project.org/web/packages/lme4/index.html

Bland, J. M., & Altman, D. G. (2000). The odds ratio. *BMJ*, *320*(7247), Article 1468. https://doi.org/10.1136/bmj.320.7247.1468

Bradley, J. V. (1978). Robustness? *British Journal of Mathematical and Statistical Psychology*, *31*(2), 144–152. https://doi.org/10.1111/j.2044-8317.1978.tb00581.x

Card, D., & Giuliano, L. (2016). Universal screening increases the representation of low-income and minority students in gifted education. *Proceedings of the National Academy of Sciences*, *113*(48), 13678–13683. https://doi.org/10.1073/pnas.1605043113

Carman, C. A., & Taylor, D. K. (2010). Socioeconomic status effects on using the Naglieri Nonverbal Ability Test (NNAT) to identify the gifted/talented. *Gifted Child Quarterly*, *54*(2), 75–84. https://doi.org/10.1177/0016986209355976

Daniels, V. I. (1998). Minority students in gifted and special education programs: The case for educational equity. *The Journal of Special Education*, *32*(1), 41–43. https://doi.org/10.1177/002246699803200107

Domina, T., Pharris-Ciurej, N., Penner, A. M., Penner, E. K., Brummet, Q., Porter, S. R., & Sanabria, T. (2018). Is free and reduced-price lunch a valid measure of educational disadvantage? *Educational Researcher*, *47*(9), 539–555. https://doi.org/10.3102/0013189X18797609

Donovan, M. S., & Cross, C. T. (Eds.). (2002). *Minority students in special and gifted education*. National Academies Press.

Dupraz, Y. (2013). *Using weights in Stata*. http://www.parisschoolofeconomics.eu/docs/dupraz-yannick/using-weights-in-stata.pdf

Erwin, J. O., & Worrell, F. C. (2012). Assessment practices and the underrepresentation of minority students in gifted and talented education. *Journal of Psychoeducational Assessment*, *30*(1), 74–87. https://doi.org/10.1177/0734282911428197

Esquierdo, J. J., & Arreguín-Anderson, M. (2012). The "invisible" gifted and talented bilingual students: A current report on enrollment in GT programs. *Journal for the Education of the Gifted*, *35*(1), 35–47. https://doi.org/10.1177/0162353211432041

Faraway, J. J. (2014). *Linear models with R* (2nd ed.). CRC Press.

Florida Department of Education. (2017a). *PK-20 education information portal*. https://edstats.fldoe.org/SASPortal/main.do

Florida Department of Education. (2017b). *PK-20 data warehouse*. http://www.fldoe.org/accountability/data-sys/edw/

Florida Department of Education. (2019). *Definitions*. https://edstats.fldoe.org/portal%20pages/Documents/Definitions.pdf

Ford, D. (2014). Segregation and the underrepresentation of blacks and Hispanics in gifted education: Social inequality and deficit paradigms. *Roeper Review*, *36*(3), 143–154. https://doi.org/10.1080/02783193.2014.919563

Gentry, M., Fugate, C. M., Wu, J., & Castellano, J. (2014). Gifted Native American students—Literature, lessons, and future directions. *Gifted Child Quarterly*, *58*(2), 98–110. https://doi.org/10.1177/0016986214521660

Goings, R. B., & Ford, D. Y. (2018). Investigating the intersection of poverty and race in gifted education journals: A 15-year analysis. *Gifted Child Quarterly*, *62*(1), 25–36. https://doi.org/10.1177/0016986217737618

Grissom, J. A., & Redding, C. (2015). Discretion and disproportionality: Explaining the underrepresentation of high-achieving students of color in gifted programs. *AERA Open*, *2*(1), 1–25. https://doi.org/10.1177/2332858415622175

Grissom, J. A., Redding, C., & Bleiberg, J. F. (2019). Money over merit? Socioeconomic gaps in receipt of gifted services. *Harvard Educational Review*, *89*(3), 337–369. https://doi.org/10.17763/1943-5045-89.3.337

Hodges, J. (2018). Assessing the influence of No Child Left Behind on gifted education funding in Texas: A Descriptive Study. *Journal of Advanced Academics*, *29*(4), 321–342. https://doi.org/10.1177/1932202X18779343

Hodges, J. (2020). Using state data to conduct research in the field of gifted education. *Journal of Advanced Academics*, *31*(1), 3–13. https://doi.org/10.1177/1932202X19881436

Hodges, J., McIntosh, J., & Gentry, M. (2017). The effect of an out-of-school enrichment program on the academic achievement of high-potential students from low-income families. *Journal of Advanced Academics*, *28*(3), 204–224. https://doi.org/10.1177/1932202X17715304

Hodges, J., Tay, J., Desmet, O., Ozturk, E., & Pereira, N. (2018). The effect of the 2008 recession on gifted education funding across the State of Texas. *AERA Open*, *4*(3), 1–11. https://doi.org/10.1177/2332858418786224

Hodges, J., Tay, J., Lee, H., & Pereira, N. (2019). The influence of the Great Recession on the identification of students from non-White populations in the State of Texas. *Journal of Advanced Academics*, *30*(2), 124–143. https://doi.org/10.1177/1932202X19825802

Hodges, J., Tay, J., Maeda, Y., & Gentry, M. (2018). A meta-analysis of gifted and talented identification practices. *Gifted Child Quarterly*, *62*(2), 147–174. https://doi.org/10.1177/0016986217752107

Ihrig, L. M., Lane, E., Mahatmya, D., & Assouline, S. G. (2018). STEM excellence and leadership program: Increasing the level of STEM challenge and engagement for high-achieving students in economically disadvantaged rural communities. *Journal for the Education of the Gifted*, *41*(1), 24–42. https://doi.org/10.1177/0162353217745158

Kettler, T., Puryear, J. S., & Mullet, D. R. (2016). Defining rural in gifted education research: Methodological challenges and paths forward. *Journal of Advanced Academics*, *27*(4), 245–265. https://doi.org/10.1177/1932202X16656896

Konstantopoulos, S., Modi, M., & Hedges, L. V. (2001). Who are America's gifted? *American Journal of Education*, *109*(3), 344–382. https://doi.org/10.1086/444275

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26.

Lamb, K. N., Boedeker, P., & Kettler, T. (2019). Inequities of enrollment in gifted education: A statewide application of the 20% equity allowance formula. *Gifted Child Quarterly*, *63*(4), 205–224. https://doi.org/10.1177/0016986219830768

Makel, M. C., & Plucker, J. A. (2017). *Toward a more perfect psychology: Improving trust, accuracy, and transparency in research*. American Psychological Association.

Matthews, M. S. (2007). Assessing the impact of a proposed rule change on the identification of gifted English language learners. *Gifted Children*, *2*(1), Article 5.

Matthews, M. S., & Shaunessy, E. (2010). Putting standards into practice: Evaluating the utility of the NAGC pre-K–Grade 12 gifted program standards. *Gifted Child Quarterly*, *54*(3), 159–167. https://doi.org/10.1177/0016986209356708

McBee, M. T. (2006). A descriptive analysis of referral sources for gifted identification screening by race and socioeconomic status. *Journal of Secondary Gifted Education*, *17*(2), 103–111. https://doi.org/10.4219/jsge-2006-686

McBee, M. T., Shaunessy, E., & Matthews, M. S. (2012). Policy matters: An analysis of district-level efforts to increase the identification of underrepresented learners. *Journal of Advanced Academics*, *23*(4), 326–344. https://doi.org/10.1177/1932202X12463511

Montgomery, D. (2001). Increasing Native American Indian involvement in gifted programs in rural schools. *Psychology in the Schools*, *38*(5), 467–475. https://doi.org/10.1002/pits.1035

Naglieri, J. A., & Ford, D. Y. (2003). Addressing underrepresentation of gifted minority children using the Naglieri Nonverbal Ability Test (NNAT). *Gifted Child Quarterly*, *47*(2), 155–160. https://doi.org/10.1177/001698620304700206

National Center for Educational Statistics. (2016). *Common core of data: Identification of rural locales*. http://nces.ed.gov/ccd/rural_locales.asp#justification

Peters, S. J., Gentry, M., Whiting, G. W., & McBee, M. T. (2019). Who gets served in gifted education? Demographic representation and a call for action. *Gifted Child Quarterly*, *63*(4), 273–287. https://doi.org/10.1177/001698621983373

Plucker, J. A., Burroughs, N., & Song, R. (2010). *Mind the (other) gap! The growing excellence gap in K-12 education*. Center for Evaluation and Education Policy, Indiana University.

R Core Team. (2017). *R: A language and environment for statistical computing*. Vienna, Austria.

Rasheed, M. (2020). Context and content in rural gifted education: A literature review. *Journal of Advanced Academics*, *31*(1), 61–84. https://doi.org/10.1177/1932202X19879174

Seber, G. A., & Lee, A. J. (2012). *Linear regression analysis* (Vol. 936). John Wiley & Sons.

Stambaugh, T., & Ford, D. Y. (2015). Microaggressions, multiculturalism, and gifted individuals who are Black, Hispanic, or low income. *Journal of Counseling & Development*, *93*(2), 192–201. https://doi.org/10.1002/j.1556-6676.2015.00195.x

U.S. Census Bereau. (2012). *Florida: 2010*. https://www2.census.gov/library/publications/decennial/2010/cph-2/cph-2-11.pdf

Warne, R. T., Anderson, B., & Johnson, A. O. (2013). The impact of race and ethnicity on the identification process for giftedness in Utah. *Journal for the Education of the Gifted*, *36*(4), 487–508. https://doi.org/10.1177/0162353213506065

Xu, R. (2003). Measuring explained variation in linear mixed effects models. *Statistics in Medicine*, *22*(22), 3527–3541. https://doi.org/10.1002/sim.1572

Yoon, S. Y., & Gentry, M. (2009). Racial and ethnic representation in gifted programs: Current status of and implications for gifted Asian American students. *Gifted Child Quarterly*, *53*(2), 121–136. https://doi.org/10.1177/0016986208330564

About the Authors

Jaret Hodges is an assistant professor at the University of North Texas. His research interests are in gifted education policy, gifted education in rural schools, and underrepresentation in gifted education programs.

Marcia Gentry directs the Gifted Education Research and Resource Institute at Purdue University, where she enjoys working with doctoral students and engaging in research and gifted education professional development. She remains active in the field through service to NAGC and AERA and by writing, reviewing, and presenting research aimed to improve education for children, youth, and teachers. She focuses on underserved populations and creating an equitable, socially just field.