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Predictors of Access to Gifted Education: What Makes for a Successful School?

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Abstract

A wide research base has documented the disproportional enrollment in K-12 special education and gifted and talented services across racial and socioeconomic lines. This study extends that knowledge base by integrating multiple population-level datasets to better understand predictors of access to and enrollment in gifted and talented services and tested whether these variables remained predictive after controlling for state mandate to provide services, average district achievement, and average school achievement. Results showed that states varied, with some serving 20% of their students as gifted and others serving 0%. Similarly, within-district income segregation, income-related achievement gaps, and parental education were dominant predictors of a school offering gifted and talented services and the size of the population served, even after controlling for achievement and the presence of a state mandate. These findings suggest that gifted and talented programs are often made available based on school or community demographics rather than the needs of the students.

Keywords

equity, gifted, segregation, talented

Advanced educational opportunities have been a fixture of the American educational system since the early 20th century. Within this larger category of services are K-12 gifted and talented (GT) programs; accelerated K-12 coursework, where students take courses earlier or faster than is typical; dual-enrollment courses, where students are enrolled in college courses while still in high school; and stand-alone, exam-based selective high schools. These services are unique regarding access and availability because they are not universally mandated across or within states in the same way as services for students with disabilities (special education) or those from low-income families (Title 1). Instead, states, districts, and even individual schools make choices on what they offer based on criteria that are not well understood or standardized.

Access to Gifted and Talented Services

According to the 2018–2019 State of the States of Gifted Education Report (Rinn et al., 2020), 24 states mandate gifted programming or services and 11 leave the decision to individual school districts. Similarly, 38 states mandate the identification of gifted and talented students, although only eight of those states prescribe the specific identification process to be used. Just

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focusing on mandated identification and mandated services, there is wide diversity in what happens across and within states. The result is highly-variable availability of services depending partly on where students live or the particular school they attend.

Programs for GT students have long been disproportionately enrolled by students from White, Asian American, and upper-income families (Grissom et al., 2019; Yoon & Gentry, 2009). In a 2019 article based on the 2014–2015 U.S. Office of Civil Rights Data, Peters et al. found that 42% of American schools identified zero students as GT, including schools in states with mandated identification policies. For example, despite relatively strong state mandates, Alabama, New Mexico, and Ohio reported 30%, 26%, and 28% of schools as having zero identified students. For academically-focused GT services, this might be defensible if all students at these schools were already perfectly challenged and thus required no advanced learning services. In such a case, school achievement would strongly predict access. Gentry et al. (2019) disaggregated the same OCR data and showed that 61% of Title I schools provided access to gifted services while only 56% of non-Title I schools did so. Students of color (Black and Latinx[1]) were those most disadvantaged by a lack of access. Specifically, Peters et al. found that Black and Latinx students were represented in K-12 gifted programs at rates of only 57% and 70%, respectively, compared to their representation in the larger K-12 population. Students who were still learning English or receiving special education services showed even lower representation rates (0.27 and 0.21 respectively).

Gentry et al. (2019) noted that the population of students who have access to school-based GT programs does not mirror the larger student population. The authors operationalized a school as providing access if it had at least one student identified as being served by a GT program. Extrapolating the identification rates from schools that did provide access to those that did not, they calculated that anywhere from 63% to 74% of Black students and 53% to 66% of Latinx students were going unserved, specifically because they attended schools that did not offer GT services. This finding highlights a lack of understanding as to why schools choose to offer GT services and whether or not school-level differences related to demographics or achievement can explain access and enrollment differences, or if some larger state, district, or family-level factors are at play.

Absent strong, consistently-enforced policies, parents can use their cultural or socioeconomic capital to gain advantages (Walsh, 2008). These advantages can be deployed through deliberate choices by parents to prepare their children to do well in the selection process, or even directly intervening with teachers or administrators to influence their child's chances of getting into the program. This latter option can take the form of parents appealing negative placement decisions or soliciting outside private testing available only to families with financial capital. These parental behaviors are consistent with work that finds well-off parents carefully planning and negotiating advantages for their children through direct contact with schools or by marshaling resources to give their children experiences that help them in schooling (Calarco, 2018; Lareau, 2011; Murray et al., 2020). This direct intervention tactic is effective. Walsh (2008) found that parental lobbying was a successful mechanism to get a child into a GT program and that the result was an increase in the false negative rate as otherwise deserving students were "crowded out" from the program.

Even within states that mandate it, the lack of consistent access to GT points to a lack of understanding of what motivates a school or district to offer such services. Districts may be using these programs as attractions for families who might otherwise leave the district. A 2019 article in the *New York Times* noted that if gifted programs in New York City were discontinued, wealthy White and Asian American families might leave the district, resulting in an even-more segregated school system (Shapiro, 2019). Davis et al. (2010) showed a strong quasi-experimental basis for such a concern. Among students who did not receive free or reduced-price lunch (FRL), those who scored above the cutoff for admission to gifted services were more likely to remain in the district in the following year than those who scored just below. This suggests that student need for the service is not the sole factor driving its availability.

Gifted and Talented Policy

Who is identified for GT has been studied more than where GT services are available (i.e., access). Grissom and Redding (2016) applied a conditional probability approach to understanding the state of disproportionality in gifted education via the Early Childhood Longitudinal Study (both the ECLS:K-1999 and ECLS:K-2011 cohorts). They found that approximately 7% of White students and 14% of Asian American students were identified as gifted by third grade compared to only 2% of Black and 5% of Latinx students. However, their study differed from Peters et al. (2019) because Grissom and Redding included a range of additional predictor variables in their multi-level regression. Specifically, after accounting for student-level achievement in mathematics and reading, the identification gap between White and Latinx students was statistically insignificant, as was the gap between Asian American and White students. However, even controlling for achievement, sex, socio-economic status (SES), health, and age at school entry did little to change the Black–White identification gap. Black students remained about half as likely to be identified as similar-achieving, similar-SES, White peers.

Although the Grissom and Redding (2016) study was exceptional in its use of a wide range of student-level covariates, the ECLS-K dataset does not allow researchers to understand if students were not identified because of lack of access (i.e., they attend a school that offers no GT services) or because they did not meet actual criteria for identification. The state, district, or school in which the student is enrolled and a number of other district- or school-specific criteria are likely predictive of identification.

In one of the few papers to evaluate the effect of particular state policies on GT access, Hodges and Lamb (2019) analyzed historical data from Washington state from 2006–2013 to evaluate the effect of the 2008 financial crisis, and changes to state accountability rules for GT that followed, on the availability of GT services. Across that time period, the percentage of schools offering GT services declined from 77% to 62%, even in the presence of a state mandate. Interestingly, 80% of the school districts discontinuing services did not make adequate yearly progress in increasing student achievement under No Child Left Behind, pointing to low average achievement at the school level as a likely predictor. Similarly, Hodges et al. (2019) showed that the budget cuts due to the great recession did not affect Texas' overall GT identification rate. This was true for Black and Latinx students as well as White students, suggesting that, overall, school funding levels are not a major driver of access. Texas and Washington are similar in two important ways: (1) they provide per-pupil funding for students identified as gifted, thereby incentivizing the provision of gifted services; and (2) they legally mandate such services.

Texas served as the context for a natural experiment on the effects of gifted education and policy oversight due to changing legal requirements and enforcement between 1999 and 2013 (Warne & Price, 2016). Texas made two changes to state law related to gifted education. In 2003, Texas terminated the prior state mandate that included on-site audits by teams of external evaluators. This resulted in 6 years of no mandated gifted education services. Then, in 2009, gifted identification and services were again mandated, but without the audits. These changes resulted in an ideal natural experiment on the effects of different policy mandates on the availability of services.

The results from Warne and Price (2016) were relatively clear: When accountability systems were removed, the percentage of students identified in the state decreased and the percentage of schools with zero gifted students increased. Although these changes were relatively small, when taken in the context of other research on the effects of state policies in other areas of K-12 education, they suggest that legal mandates and oversight influence the availability of services and the size of the population identified in each school.

Current Study

The present study sought to understand what state, district, and school-level variables were associated with greater access to and enrollment in GT at the school level. As the field of K-12 education better understands what variables are associated with access, it can then begin to mitigate barriers and improve equity. This study is unique in that it incorporated data from several population-level datasets to investigate what variables at the state, district, and school levels made for a successful, equitable school for advanced learners. The overall goal of this study was exploratory: to understand what state, district, and school-level variables were most associated with access to GT and the percentage of a school and state served by GT. Specifically, we posed the following research questions:

1. What is the general distribution of GT access and enrollment and how does this distribution vary by level (school, district, or state)?
2. How do segregation, school and district demographics, and student achievement correlate with GT access and enrollment?
3. How do these relationships (#2) change when controlling for the presence of legal mandates to provide access to GT, average district achievement, and average school-level achievement?

Methods

Data Sources

To answer our research questions, we merged data from several population-level datasets:

- The biannual United States Office of Civil Rights Data Collection (OCR) is the only source for information on the GT identification rates for every school and district. This study used the 2017–2018 public OCR data, released October 15, 2020.
- The National Center for Education Statistics (NCES) Common Core of Data (CCD) is an annual database of nearly all public schools and school districts in the United States. Information about school demographics and the distribution of students across districts came from the CCD.
- The Stanford Education Data Archive Version 3.0 (SEDA; Reardon et al., 2017) provided school-level and district-level measures of average achievement and achievement gaps for student subgroups in Grades 3–8 for the 2015–2016 school year. Built from the Department of Education's EDFacts data and National Assessment of Education Progress, these data provided a way to compare student achievement across school districts and states.
- The NCES' Education Demographic and Geographic Estimates (EDGE) project data from the American Community Survey and the decennial Census onto areas contiguous with school district boundaries. These data described district-level social and economic conditions and were included as district-level independent variables.
- State-level Policies for Gifted Education are taken from the National Association for Gifted Children 2018–2019 State of the States Report (Rinn et al., 2020). This allowed us to assign a dichotomous variable to each state for whether that state mandated the identification of gifted and talented students as of the 2019–2020 academic year. Importantly, we cross-checked this data file with past State of the State reports (e.g., 2015) in order to determine policies in place in the 2017–2018 year, from which OCR

> data were drawn. In cases where there was disagreement, we reviewed state laws and contacted state education officials before deciding whether the state mandated identification. In the end we coded 12 states as not having a mandate (DC, CA, IL, MA, MI, NH, NY, ND, RI, SD, UT, VT).

We merged all of the individual datasets resulting in a cross-sectional data file for nearly all public schools in the United States for the 2017–2018 school year. For the 2017–2018 OCR data collection, 99.81% of LEAs with 99.9% of schools certified their submissions. This included 17,604 LEAs and 97,632 schools. OCR also suppresses certain data, but for the 2017–2018 year, none of these included the variables used in our analyses. All analyses and data management were conducted in Stata (Version 16).

Exclusion Criteria

As noted above, the OCR dataset includes nearly all school districts in the United States. For our analyses, we used all public schools (not private). However, some schools were excluded from our analyses. These included 602 Juvenile Justice schools (0.62% of the dataset), 4,123 magnet schools (4.22%), 7,049 charter schools (7.22%), and 3,343 "alternative" schools (3.42%). An alternative school was defined as:

> A public elementary or secondary school that addresses the needs of students that typically cannot be met in a regular school program, and is designed to meet the needs of students with academic difficulties, students with discipline problems, or both students with academic difficulties and discipline problems. (U.S. Office of Civil Rights, n.d., p. 8)

Note that some of these classifications overlapped. The result was a reduction in analytic sample of 13.89%. We excluded these sites due to the inconsistency across states of whether these types of schools must meet the same legal mandates and general policies for services as traditional schools.

Variables

While this study was exploratory in nature, the independent variables were all chosen because of a range of prior research showing the correlation between them and common academic outcomes of disproportionality in use of school discipline (Shores et al., 2020; United States Government Accountability Office [USGAO], 2018), receipt of special education services (Farkas et al., 2020; Strand & Lindorff, 2021), and GT identification rates (Grissom & Redding, 2016; Grissom et al., 2019; Hamilton et al., 2018). Below is a short description of the different types of independent variables:

Segregation. We used measures of segregation as provided in the SEDA covariate files. These Thiel information theory indices are measures that compare a school's diversity to the diversity of the school's district. Our analyses standardized these measures to have mean 0 and standard deviation 1 with smaller values representing less within-district segregation and larger values representing more. There are segregation variables for White–Black segregation, White–Hispanic segregation, and Free/Reduced Price Lunch–Non Free/Reduced Price Lunch segregation. Shores et al. (2020) found that segregation variables were strong predictors of achievement gaps and school discipline gaps.

Achievement. Achievement measures are taken from the SEDA 3.0 (Reardon et al., 2017). Achievement and achievement gaps at the school and district level are measured in standard deviation units. Also, from the SEDA, we included measures of district achievement gaps including White–Black, White–Hispanic, White–Asian, and Economic Disadvantage–Non Economic Disadvantage.

Demographics. From the CCD, school-level demographics included the proportion of each school's enrollment that was Black, White, Hispanic, Asian, and eligible for FRL. Additionally, we used the SEDA SES composite and the proportion of adults living in the geographic area of each LEA that have Bachelor's (or higher) degrees. The SEDA SES variable is a composite of each community's median income, percentage of adults 25 and older with a college degree, child poverty rate, percentage of households receiving supplemental nutrition benefits, percentage of households with single mothers, and the adult employment rate taken from the American Communities Survey.

Table 1 presents the independent variables in our analyses and their respective means and standard deviations.

Dependent Variables

Our two dependent variables were whether a school provided access to GT services (coded as 0/1) and, for those that did, the percent of the school's student population that was served by GT. The former was operationalized by the OCR question that asked whether any students were served in GT. If a school replied yes, then they were asked for enrollment numbers. Enrollment numbers in GT were then used as the numerator when calculating the percent of a school served by GT. In this fashion, throughout this paper, schools are referred to as providing "access" if they reported > 0 students identified as gifted. This is imperfect since it is plausible that some schools truly have zero GT students, even in the presence of access.

One limitation to the public OCR file is that outcomes are subjected to random perturbing (U.S. Department of Education [USDOE], 2020). Student count data (including GT counts) had one case added or subtracted and used random data swapping to protect student privacy. However, this perturbing was bound as not to exceed the total number of instances or total enrollment in a class. This means that if a school had 25 GT students, then the perturbing for GT students would not exceed 25. Importantly, none of this perturbing or masking of data in the public file applied to the question related to whether a school had any students served by GT. True zeros were maintained in the public dataset except for outcome data. Only the counts for GT enrollment were subject to perturbing, but as it was done at random it would have only minor effects on attenuating correlations.

Data Analysis

American K-12 schools exist within national, state, district, and individual school contexts. Of these, only national policies apply to all schools, but national policies for GT are all but nonexistent. For this reason, we implemented a three-level, mixed-effects linear probability model (LPM) of schools nested within districts nested within states. We preferred the LPM to mixed effects logistic regression as the resulting coefficients are directly interpretable as mean marginal effects (Wooldridge, 2010). Hellevik (2009) argued that this approach is superior and preferable to that of logistic regression, particularly because the violation of the homoscedasticity assumption appears to have little effect on the results. Still, to be cautious, we applied heteroskedastic-robust standard errors to ameliorate this issue in the range of 0–1. To establish the baseline level and distribution of the variation in our dependent variables, we estimated the following three-level unconditional model with dependent variables measured for each school i in district j in state k (RQ1):

$$Y_{ijk} = \pi_{0jk} + e_{ijk},\ e_{ijk} \sim N(0, \sigma_e^2) \quad (1)$$

$$\pi_{0jk} = \beta_{00k} + r_{0jk},\ r_{0jk} \sim N(0, \tau_\pi^2) \quad (2)$$

$$\beta_{00k} = \gamma_{000} + u_{00k},\ u_{00k} \sim N(0, \tau_\beta^2) \quad (3)$$

The intraclass correlations (ICC) of these models allowed us to quantify the level of variation in each outcome observed at school, district, and state level. Following these basic descriptives at each level, we built models to understand simple correlations between state-, district-, and school-level independent and our dependent variables. To do so we estimated models of the following form—changing the outcome variables one at a time and interpreting the fixed effects from these models—to answer our research questions:

$$Y_{ijk} = \pi_{0jk} + \pi_{1jk}([Variable]_{ijk}) + e_{ijk} \quad (4)$$

$$\pi_{0jk} = \beta_{00k} + r_{0jk} \quad (5)$$

$$\pi_{1jk} = \beta_{10k} + \beta_{11k}([Variable]_{1jk}) + r_{1jk} \quad (6)$$

$$\beta_{00k} = \gamma_{000} + u_{00k} \quad (7)$$

$$\beta_{10k} = \gamma_{100} + \gamma_{101}([Variable]_{10k}) + u_{10k} \quad (8)$$

$$\beta_{11k} = \gamma_{110} \quad (9)$$

Each model contains one independent variable (e.g., school proportion Black), and we estimated models on the full set of independent variables (see Table 1) for each dependent variable. This resulted in a series of bivariate correlations between each outcome and each independent variables (RQ2). We did this not only to understand simple correlations, but also because these initial models served as a baseline through which the conditional predictive probability models addressing RQ3 could be compared.

Lastly, to address RQ3, we tested models with all of the same independent variables as above but after controlling for legal mandate for GT (Model 1), the average achievement of the district (Model 2), the average achievement of the school (Model 3), or all three (Model 4). This allowed us to evaluate the degree to which each of these three controls (GT mandate, school achievement, district achievement) moderated the relationships between our independent variables and our GT dependent variables. We controlled for these variables because of their expected relationship with both service availability and enrollment. For example, we expected that whether or not a school existed in a state with a legal mandate to provide GT access would explain much of the variability in both the percentage of schools offering GT services as well as the percentage of students served. Similarly, we expected district- and school-level achievement to explain the percentage of a school served by GT. Controlling for state mandates allowed us to test which variables remained relevant in explaining which schools have access to or enrolled larger percentages of students in GT. While one of our dependent variables was dichotomous (access) and the other was continuous (proportion of students served by GT), both were analyzed with the same LPM. More on the interpretation of these models is included in the next section.

Results

First, we calculated intraclass correlations for both of our outcome variables with schools nested in districts nested in states. The result was that 31% of the variance in whether or not a school offered GT fell at the school level with 28% at the district and 41% at the state levels. The high state ICC makes intuitive sense given many states have mandates for schools to provide access. The variance in the proportion of a school served by GT fell more at the individual school level (46%), with a similar amount at the district level (41%), and very little at the state level (13%). Again, this makes intuitive sense since states might mandate access, but it is the achievement or ability of the students at a given school that determines the percent of that school identified as GT. These large ICCs make it clear that the nested structure was important to understanding our relationships of interest.

To better understand how GT opportunities are distributed across states, districts, and schools (RQ1), we calculated the percentage of schools that provided access to GT services, the average proportion of students served in schools that do provide access, and the overall proportion of a state's population served. These results are presented in Table 2.

Table 2 shows wide variability in both access to and enrollment in GT across states. For example, in 2017–2018, North Carolina had the highest percentage of schools providing access (96.2%). Similarly, among those schools offering GT, Kansas had the highest average school proportion served (22%). Finally, Maryland had the greatest proportion of its K-12 student population served as GT (19%). It is important to consider the

Table 1. Variable Descriptive Statistics

Variable Description	Variable	Mean	*SD*
LEA White-Black segregation	wb_seg	0.111	0.138
LEA White-Hispanic segregation	wh_seg	0.089	0.109
LEA FRL segregation	frl_seg	0.065	0.076
Average school achievement	s_ach	−0.003	0.408
Average district achievement	l_ach	−0.002	0.333
LEA White-Asian achievement gap	l_ach_wag	−0.158	0.276
LEA White-Black achievement gap	l_ach_wbg	0.595	0.246
LEA White-Hispanic achievement gap	l_ach_whg	0.446	0.240
LEA Economic achievement gap	l_ach_neg	0.564	0.200
School percent White	pct_wht	0.598	0.331
School percent Asian	pct_asn	0.039	0.083
School percent Hispanic	pct_hsp	0.204	0.258
School percent Black	pct_blk	0.139	0.224
School percent FRL	pct_frl	0.509	0.255
LEA SES	lea_ses	0.120	0.936
LEA percent parents with college degree	lea_baplus	0.268	0.136
State gifted mandate	st_gt_law	0.731	0.443

percentage of schools providing access when reviewing the next two columns. For example, Illinois has only 3.8% of its students served by GT programs, but part of that is because only 21% of Illinois schools reported serving > 0 students as GT. If more schools provided access, it is likely that the percentage of students served by GT in Illinois would increase. Given that some of the states with the largest Black populations are also the states with low percentages of access (e.g., CA, NY, IL, MA), this is a significant equity issue.

Research Question 2 focused on state, district, and school correlates of access to and enrollment in GT. Table 3 presents these estimates with the independent variables broken down by segregation, achievement, and demographics. Note that while Table 1 reports the three within-LEA segregation variables on their original scale, for the following analyses they were standardized to a mean of 0 and a standard deviation of 1 to aid in interpretation. For example, a school being located in a district with high levels of White–Black segregation (+1SD) is associated with a 5 percentage-point increase in probability of access. This is a different interpretation than with more common odds ratios. Put differently, a given school located in a district with low levels of within-district White–Black segregation (−1SD) is predicted to have a 10 percentage-point lower probability of having access compared to a similar school in a highly-segregated district (+1SD).

Within Table 3, the independent variables are represented by different units. For this reason, direct comparisons between size of parameter estimates are most valid within each category. For example, White-–Black segregation is only 60% as strong a predictor of GT access as FRL-segregation (0.05 vs. 0.084). As a reminder, the segregation variables have been standardized such that the coefficients represent the relationship between the outcome variables and a one standard deviation increase in segregation, with larger values indicating more segregated districts (those where the schools look less like the overall district demographics). Among achievement variables, school-level achievement had the strongest correlation with proportion served by GT (0.102), while the LEA FRL achievement gap had by far the strongest relationship with access (0.308). This latter finding means that schools with an above-average level of FRL segregation (+1SD) in their districts were 31 percentage points more likely to have access to GT. Other noteworthy findings are the positive relationship between the school proportion Asian with access and enrollment (0.254, 0.234) and the negative

Table 2. Schools Offering GT by State, Percent of Average School Enrolled, and Percent of State Served

State	% of Schools With Access	% of Average School Identified	% of State Identified
AK	44.7%	6.7%	5.0%
AL	71.3%	8.6%	6.1%
AR	92.9%	10.0%	9.5%
AZ	69.3%	7.2%	5.7%
CA	63.4%	7.4%	6.5%
CO	89.2%	6.5%	7.6%
CT	33.7%	6.1%	2.2%
DC	0.0%	0.0%	0.0%
DE	29.1%	5.9%	1.6%
FL	90.6%	6.4%	6.4%
GA	95.6%	9.2%	10.6%
HI	30.7%	3.9%	1.2%
IA	93.1%	10.8%	10.0%
ID	55.3%	5.7%	3.7%
IL	20.8%	14.2%	3.8%
IN	84.4%	12.6%	12.4%
KS	77.2%	22.0%	14.2%
KY	92.2%	13.6%	13.4%
LA	78.1%	4.0%	3.8%
MA	2.8%	15.0%	0.5%
MD	87.0%	16.8%	19.0%
ME	72.0%	6.6%	5.5%
MI	9.8%	10.9%	1.5%
MN	45.5%	14.7%	9.2%
MO	59.9%	5.1%	4.0%
MS	72.5%	8.9%	6.5%
MT	25.1%	6.7%	3.3%
NC	96.2%	10.2%	11.2%
ND	17.1%	7.0%	1.8%
NE	71.8%	11.8%	11.0%
NH	7.0%	10.2%	0.9%
NJ	55.2%	9.5%	5.6%
NM	74.8%	4.5%	4.7%
NV	63.2%	4.6%	2.6%
NY	12.9%	10.9%	1.7%
OH	73.6%	10.5%	8.6%
OK	94.2%	14.1%	14.4%
OR	84.5%	56%	6.8%
PA	87.5%	3.5%	3.7%
RI	2.2%	11.9%	0.2%
SC	91.2%	14.4%	15.5%
SD	9.1%	7.1%	1.8%
TN	52.7%	2.8%	1.6%
TX	94.9%	7.9%	8.3%
UT	30.4%	14.5%	5.8%
VA	94.4%	12.4%	13.5%
VT	1.7%	8.6%	0.1%
WA	78.7%	6.2%	5.9%
WI	47.9%	7.8%	4.9%
WV	76.5%	2.4%	1.9%
WY	28.8%	8.1%	2.8%

Table 3. Bivariate Correlations Between Predictors and GT Access and Enrollment

	Access[a]	Enrollment[a]
Segregation Variables		
White-Black segregation—Std	0.050 (0.006)***	0.001 (0.002)
White-Hispanic segregation—Std	0.059 (0.005)***	0.001 (0.002)
FRL segregation—Std	0.084 (0.005)***	0.005 (0.002)***
Achievement variables		
School level achievement	0.102 (0.004)***	0.102 (0.001)***
LEA level achievement	0.163 (0.009)***	0.039 (0.004)***
LEA White-Asian gap	−0.053 (0.018)***	−0.003 (0.005)
LEA White-Black gap	0.149 (0.017)***	0.058 (0.005)***
LEA White-Hispanic gap	0.146 (0.017)***	0.035 (0.006)***
LEA economic gap	0.308 (0.017)***	0.056 (0.007)***
Demographic variables		
School proportion White	0.079 (0.007)***	0.120 (0.002)***
School proportion Asian	0.254 (0.021)***	0.234 (0.008)***
School proportion Hispanic	−0.013 (0.008)	−0.112 (0.003)***
School proportion Black	−0.120 (0.008)***	−0.099 (0.003)***
School proportion FRL	−0.126 (0.006)***	−0.176 (0.002)***
LEA SES	0.051 (0.003)***	0.010 (0.001)***
LEA proportion college	0.438 (0.022)***	0.090 (0.009)***

Note. [a](b/se).
***$p < .001$.

relationship between school proportion Hispanic, Black, or FRL and access (−0.013, −0.12, −0.126). Parental college education (proportion of adults in the LEA with a college degree) also emerged as a strong correlate of access. More educated communities had a higher rate of access such that a 10 percentage-point increase in the proportion of the community that had bachelor's degrees was associated with a 4.4 percentage-point increase in predicted probability of access.

Research Question 3 moved beyond correlations to examine the effect of independent variables after controlling for whether or not the state had a mandate for gifted identification, average LEA achievement, and average school achievement. Table 4 presents the estimated coefficients regarding whether a school offered GT services. Table 5 presents the same independent variables on the outcome of the proportion of a school served by GT (for those schools that offered GT services). In each table, Model 1 controlled for whether the school was in a state with a mandate for gifted education, Model 2 added average LEA achievement, Model 3 substituted school average achievement for district achievement, and Model 4 included both LEA and school average achievement as well as state GT mandate. Each model tests the inclusion of different covariates in an exploratory fashion.

We removed school- and LEA-level achievement as independent variables in Tables 4 and 5 as they were now included as covariates in Models 2, 3, and 4. This allowed for a more direct evaluation of whether school- or LEA-level achievement explained GT access at the school level. These tables are best interpreted by moving from Model 1 to Model 2 and Model 4 (controlling for mandate, adding LEA average achievement, adding school-level achievement) or by moving from Model 1 to Model 3 to Model 4 (controlling for mandate, adding school achievement, adding LEA achievement). In this way the addition of each covariate can be tested in terms of change to individual predicted probability. For example, in Table 4, moving across models clarifies that none of the three covariates has much of an effect on the explanatory power of within-district FRL segregation. The parameter estimates are almost identical for all four models (~0.085) meaning that regardless of the presence of a mandate, achievement of

Table 4. Conditional Predictors of Access to School-Level Gifted and Talented Services

Variables	Model 1	Model 2	Model 3	Model 4
Segregation				
White-Black segregation—Std	0.050 (0.006)***	0.063 (0.006)***	0.054 (0.006)***	0.061 (0.006)***
White-Hispanic segregation—Std	0.059 (0.005)***	0.073 (0.005)***	0.065 (0.006)***	0.071 (0.006)***
FRL segregation—Std	0.084 (0.005)***	0.082 (0.005)***	0.086 (0.006)***	0.085 (0.006)***
Achievement				
LEA White-Asian gap	−0.052 (0.018)***	−0.032 (0.018)*	−0.022 (0.020)	−0.016 (0.020)
LEA White-Black gap	0.150 (0.017)***	0.099 (0.018)***	0.120 (0.019)***	0.105 (0.020)***
LEA White-Hispanic gap	0.146 (0.016)***	0.098 (0.017)***	0.129 (0.018)***	0.108 (0.018)***
LEA economic gap	0.308 (0.017)***	0.241 (0.018)***	0.304 (0.018)***	0.288 (0.019)***
Demographic				
School proportion White	0.079 (0.007)***	0.053 (0.007)***	−0.047 (0.008)***	−0.049 (0.008)***
School proportion Asian	0.253 (0.021)***	0.214 (0.021)***	0.066 (0.020)***	0.066 (0.020)***
School proportion Hispanic	−0.013 (0.008)	0.007 (0.008)	0.088 (0.008)***	0.088 (0.008)***
School proportion Black	−0.120 (0.008)***	−0.100 (0.008)***	−0.038 (0.008)***	−0.040 (0.008)***
School Proportion FRL	−0.126 (0.006)***	−0.102 (0.007)***	−0.038 (0.010)***	−0.033 (0.010)***
LEA SES	0.051 (0.003)***	0.015 (0.005)***	0.030 (0.004)***	0.013 (0.006)**
LEA proportion college	0.438 (0.022)***	0.330 (0.030)***	0.365 (0.025)***	0.400 (0.033)***
Covariates in model				
State mandate	X	X	X	X
School ach			X	X
LEA ach		X		X

Table 5. Conditional Predictors of School-Level Proportion Served in Gifted and Talented Services

Variable	Model 1	Model 2	Model 3	Model 4
Segregation				
White-Black segregation—Std	0.001 (0.002)	0.005 (0.002)**	0.006 (0.002)***	0.001 (0.002)
White-Hispanic segregation—Std	0.001 (0.002)	0.005 (0.002)**	0.007 (0.002)***	0.002 (0.002)
FRL segregation—Std	0.005 (0.002)***	0.005 (0.002)***	0.004 (0.002)*	0.003 (0.002)*
Achievement				
LEA White-Asian gap	−0.003 (0.005)	0.005 (0.005)	0.016 (0.005)***	0.005 (0.005)
LEA White-Black gap	0.058 (0.005)***	0.045 (0.005)***	0.018 (0.006)***	0.041 (0.005)***
LEA White-Hispanic gap	0.034 (0.006)***	0.023 (0.006)***	0.004 (0.006)	0.021 (0.006)***
LEA economic gap	0.056 (0.007)***	0.038 (0.007)***	0.004 (0.007)	0.038 (0.007)***
Demographic				
School proportion White	0.120 (0.002)***	0.121 (0.002)***	0.005 (0.003)*	0.007 (0.003)**
School proportion Asian	0.234 (0.008)***	0.225 (0.008)***	0.043 (0.008)***	0.044 (0.008)***
School proportion Hispanic	−0.112 (0.003)***	−0.110 (0.003)***	−0.017 (0.003)***	−0.017 (0.003)***
School proportion Black	−0.099 (0.003)***	−0.095 (0.003)***	0.001 (0.003)	0.000 (0.003)
School proportion FRL	−0.176 (0.002)***	−0.185 (0.002)***	−0.074 (0.004)***	−0.077 (0.004)***
LEA SES	0.010 (0.001)***	−0.002 (0.002)	−0.017 (0.001)***	−0.002 (0.002)
LEA proportion college	0.090 (0.009)***	0.053 (0.012)***	−0.071 (0.010)***	0.043 (0.013)***
Covariates in model				
State mandate	X	X	X	X
School ach			X	X
LEA ach		X		X

the school, or average achievement of a district, schools in more economically segregated districts were more likely to have access to GT (+1SD in within-district FRL segregation results in an approximately 8.5 percentage point increase in probability of access). Alternatively, the proportion of a school that is FRL-eligible has a small effect in moving from Model 1 to Model 2 (−0.126 and −0.102), but a much larger effect moving to Models 3 and 4 (−0.102 to −0.033). This suggests that school achievement explains much more of whether a school provides access to GT services than LEA achievement. It also means that after controlling for achievement, a 10 percentage-point increase in the proportion of students eligible for FRL only decreases a school's probability of offering GT by one-third of a percentage point.

Table 5 shows that the achievement class of variables was the strongest predictor of proportion of a school served in GT. Most of the segregation variables were not statistically significant. For example, the proportion of a school eligible for FRL remained a negative predictor of the proportion of a school served by GT in Models 1 (−0.176) and 2 (−0.185), but in Models 3 and 4, the size of the estimate dropped by more than half (−0.074 and −0.077). Similarly, school proportion Black was no longer a significant predictor once school achievement was added to the model and the parameter estimates for both Models 3 and 4 rounded to 0. While the proportion of parents with a college degree remained a significant, positive predictor across all four models (0.09 in Model 1) it, too, shrank in size after school achievement was added to the model (0.043 in Model 4).

Discussion

This section outlines the major thematic findings of our analyses and how they support or contrast with past research.

Diversity of Access and Size of GT Population is the Rule

In reviewing the findings from Table 2, one clear take-away is the wide variability in *access* to GT services. In fact, the majority of schools in 19 states had zero students identified as GT. Of these 19, seven have a mandate (AK, CT, DE, MN, MT, WI, and WY). However, these seven have weakly-enforced mandates, as we will detail further below. Importantly, some of these schools and schools in the other 31 states that identified zero students likely do provide access but simply *identified* no students in 2017–2018. However, we feel confident that this is the exception and not the rule. Instead, it is likely that most of the schools with zero students had zero students because they conducted no GT identification and provided no services. This appears to support past findings by Gentry et al. (2019) who found that Title I schools were actually more likely to provide access, but that for those that did, they actually identified fewer students. Gentry et al. also noted that access varied across locales with students attending rural schools having less access than other locals in 25 states.

Not all Mandates are Created Equal

In our study we classified states as either having or not having a legal mandate for GT. However, admittedly, this oversimplifies state policy postures. For example, Iowa, North Carolina, and Wisconsin are all classified as having GT mandates and yet the percentage of schools in their respective states that provide access are 93%, 96%, and 48%. What makes Iowa and North Carolina different from Wisconsin? Accountability. Iowa and North Carolina both require LEAs to submit plans and materials to their state education departments for review and approval. Alternatively, Wisconsin has a mandate, but does little to enforce it. These policy nuances are not well captured by Table 2.

These observations appear to align with Warne and Price (2016), who saw clear changes in access after accountability systems were removed and then reinstated in the state of Texas. Peters et al. (2019) and Gentry et al. (2019) both showed that simply "having" a mandate to provide GT did not show much of an effect. However, a subjective evaluation of the states with the largest percentage of schools providing access (NC, GA, FL, IA, AR, KY, OK, TX, VA) does correlate well with those states that have proactive enforcement mechanisms for their mandates. Either funding is not provided until the state receives and approves a district's GT plan (IA), there is proactive enforcement and auditing of districts (TX), or enforcement is aided via transparency with district plans and policies made publicly available (NC, FL, VA). The effectiveness of each of these accountability mechanisms warrants further study.

Achievement Explains Some Differences, but Various Forms of Capital Still Matter

As noted in the results, some predictors of access or proportion of school served by GT shrank after controlling for LEA- and school-level achievement. Two of the best examples of this are the degree to which the proportion of a school's population that was Black predicted access or percent of students identified as GT. These estimates shrank by two thirds after controlling for achievement in Table 4 (access), and shrank to null in Model 4 of Table 5 (proportion). This means that much of the difference in rates of access and proportion served at a school due to race can be explained by school and district achievement.

Alternatively, achievement had little effect in ameliorating the effects of other predictors. With regard to predicting access (Table 4), SES, parental education, and district-level FRL segregation remained strong predictors. This seems to support observations and findings by Grissom et al. (2019) and Walsh (2008) that parents with various forms of capital can use the system to their advantage. While controlling for school and district achievement made school proportion Black less of a predictor, various forms of capital and segregation remained substantial predictors of access. Schools with educated families and those with low FRL rates in districts where other schools had high FRL rates were more likely to provide access, even after controlling for achievement. Forms of capital were less powerful when explaining the proportion of a school served as GT, the exception being parental education levels.

These findings seem to support Grissom et al. (2019) who found that having a parent in a high prestige occupation was one of the most consistent predictors of a child being identified as gifted. This would also seem to support concerns expressed by Walsh (2008) that educated parents can use their cultural capital to increase opportunities at the school attended by their children. In our study, the percentage of adults with a college degree was a consistent predictor of a school providing access to GT. Importantly, in both the present study and Grissom et al., some of the students were not identified as GT because their schools did not offer any opportunity to be identified. As shown in the first column of Table 2, Georgia, North Carolina, and Oklahoma are the only states that come close to providing universal access, which might explain why being located in the geographic South of the United States was a significant predictor of being identified as GT in Grissom et al. (2019).

Both in terms of access and, within those schools that provide access, the percentage of students identified as GT, the proportion of the school eligible for FRL was a significant and substantial negative predictor. The more low-income students at a school, the less likely that school was to provide access and, even when it did, the population of GT students was smaller. Our study also showed that the more economically segregated (FRL segregation) a district, the more likely a given school was to provide access to GT. This seems to support Hamilton et al. (2018), who found that schools with higher poverty rates had lower identification rates, even within districts. Although Hamilton et al. (2018) was referring to proportion identified as opposed to access, this finding seems to suggest that the more economically-dissimilar schools are from each other in a given district, the more likely the higher SES schools are to provide access to GT.

Regarding student race as a predictor, it is a positive finding that many decreased in magnitude after controlling for mandate and average achievement. School proportion

White, Asian, and FRL as predictors all decreased in strength after achievement was added to the model. This suggests that at least part of the differences in rates of access and the size of the identified population across groups can be explained by schools serving populations with differing average achievement levels. Assuming these GT programs are academically-focused, then it might be reasonable that they have lower GT enrollments. However, in keeping with the theme of this section, achievement did not explain every relationship, as school percentage Hispanic remained a negative predictor and percentage Asian remained a positive predictor of the proportion a population served as GT.

Grissom and Redding (2016) found that, after controlling for individual-student achievement and background demographic factors, the identification gap between Asian–White and Hispanic–White disappeared, but that it remained for Black–White. In contrast, Model 4 in Table 5 showed that, after controlling for LEA and school-level achievement, percent Black was no longer a significant predictor of the percentage of the school served as gifted, whereas percent Asian was a positive predictor and percent Hispanic was a small, negative predictor. Also, in a departure from Hamilton et al. (2018), within-district segregation—including economic segregation—were not significant predictors of the percentage of a school served by GT, despite being large predictors of access.

The predictive power of district and school achievement is relevant regarding a popular method of discussion within GT: the application of local norms to improve the diversity of the population of students identified as gifted (Lohman, 2009; Peters et al., 2021). As a mechanism of identification, applying local norms works to increase diversity by identifying students as GT based on their achievement compared to the within-school average. Doing so leverages differences in mean achievement across schools, and the fact that schools are highly segregated, to even-out identification rates across schools. This is relevant in the current context since applying local norms for GT ID would decrease—if not outright remove—the predictive value of LEA average achievement on the percent of a school identified as gifted.

Limitations

While using several, population-level datasets is a strength of this paper, it also creates an important limitation. For example, two datasets represent two independent, self-reported data collections from individual schools and districts. This creates opportunities for numbers that do not agree or were incorrectly reported. There is also the potential that the OCR dependent variables do not reflect the actual rates of GT access or identification in schools. To try and cross-validate the OCR numbers, we pulled school and district GT data from Ohio and North Carolina (since these are two states that collect such data from all school districts and make it easily accessible). Because both OCR and state data undergo some kind of blinding to protect privacy, there was never perfect agreement. For example, the North Carolina database lists Buncombe County as having 3,085 White GT students while ORC lists 2,855. Similarly, the Ohio database lists Shaw Elementary as having 30.2% of its students identified as GT while OCR lists 32.2%. Again, given that both of these data points are blinded versions of the true numbers in the individual districts, we feel confident in the data provided by OCR.

It is also important to emphasize that this paper is exploratory. From reviewing Tables 4 and 5, it is clear that many relationships were tested. This creates the possibility for Type I errors or other spurious findings. Therefore we focused on consistent trends across models or outcome variables rather than on comparing specific parameter estimates or even looking for statistical significance. This is why future research should take the form of registered reports (Reich et al., 2020) and cross-validate these findings.

Additionally, measures of FRL in National datasets flatten the distribution of students' family resources into a dichotomous measure. While this is not ideal, research suggests that there are measures of educational disadvantage that are captured by FRL that are still informative (Domina et al., 2018; Michelmore & Dynarski, 2017). Again, this points to a need for further research that better captures the degree of socioeconomic disadvantage and sociocultural capital as a predictor of access to, and enrollment in, advanced learning opportunities.

Policy Implications

One of the clearest signals from this research is the wide school-level variability of GT enrollment, even after controlling for average school achievement. This points to a need for clear, universal, and automatic enrollment mechanisms like those discussed by Dougherty et al. (2015) and put into law by states like Washington (Brazile, 2019), where students are placed in advanced courses based on achievement readiness thereby removing some of the school-level discretion. Such policies could be implemented at the state level, or they could follow proposed legislation such as the Advanced Coursework Equity Act (2021) at the Federal level, incentivizing states nationwide to implement universal placement or universal screening policies. This type of incentive or a Federal mandate could help increase the availability of GT services and narrow the variability of access. Students should be provided with GT services based on whether they would benefit from them instead of whether or not parents have the social and cultural capital to advocate for them. Universally screening students for GT eligibility has been shown to identify more students overall, particularly students from traditionally disadvantaged groups (Card & Giuliano, 2016; McBee et al., 2016). Such a policy also removes the level of teacher discretion that was correlated with the underrepresentation of Black students in Grissom and Redding (2016) and the removal of which resulted in increased identification rates in Card and Giuliano (2016). Any time parents can insert their initiative or sociocultural capital into the placement process to advantage their child, they are likely to do so, which will continue to exacerbate inequalities. In a similar finding to Calarco (2020), this suggests policies targeted at reducing the power of privileged families necessarily reduce the inequality of access to and enrollment in advanced learning opportunities.

Even prior to issues of identification and enrollment, however, the present findings showed clear issues with access and GT availability. In many of the schools that identified zero students, this was because identification is never even conducted (to say nothing of service availability). Regardless of whether or not a state has a mandate, as long as some schools are allowed to not offer GT, there will continue to be inequality of access and enrollment with students from historically disadvantaged groups being those most affected.

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Note

1. In this manuscript we tried to conform to American Psychological Association recommendations for deficit-free language. However, when different terms were used in original datasets or sources (e.g., Hispanic vs. Latinx), we deferred to the usage in the original source. For this reason, in some places we refer to Latinx and in others we refer to Hispanic.