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Gifted Identification Across the Distribution of Family Income

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Abstract

Currently, 6.1 percent of K-12 students in the United States receive gifted education. Using education and IRS data that provide information on students and their family income, we show pronounced differences in who schools identify as gifted across the distribution of family income. Under 4 percent of students in the lowest income percentile are identified as gifted, compared with 20 percent of those in the top income percentile. Income-based differences persist after accounting for student test scores and exist across students of different sexes and racial/ethnic groups, underscoring the importance of family resources for gifted identification in schools.

* Corresponding author: Nicholas J. Ainsworth, ainsworn@uci.edu. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7500420: CBDRB-FY24-CES019-010, CBDRB-FY25-0309). Spiegel was a postdoctoral scholar at Stanford University when this paper was written.

Introduction

Gifted and talented (GT) education programs are a prominent way to deliver curriculum and instruction to high-aptitude students in the U.S. GT programs now serve more than 3 million U.S. public school enrollees, or about 6.1 percent of the public-school population (Snyder et al., 2020), and provide a range of interventions including ability grouping, course acceleration, and pullout programming (Bhatt, 2011). But despite its prevalence, GT is undefined in federal law. While federal law acknowledges the potential for students to have advanced skills, there are no requirements for serving these children as there are for students with disabilities. Instead, access to GT programs is left to district or school discretion, typically occurring through teacher recommendations, verbal and non-verbal reasoning evaluations, or standardized tests (Bhatt, 2011; Hodges et al., 2018). This raises important questions about how students gain access to GT opportunities.

GT identification patterns have generated equity concerns within U.S. public schools for decades. Enrollment rates vary widely by race and ethnicity: 12.6% of Asian students, 8.1% of White students, 4.5% of Hispanic students, and 3.6% of Black students are enrolled in gifted programs (Snyder et al., 2020). Lower-income students are also less likely to be identified (Grissom et al., 2019). These differences have been attributed to a range of factors, including eligibility criteria, differential enrollment in schools with GT programs, neighborhood segregation, teacher expectations, test biases, and parental advocacy (Card & Giuliano, 2016; Grissom et al., 2019; Hodges et al, 2018).

A lack of data on parental income is the primary limitation of previous analyses attempting to understand the drivers of GT identification. Prior studies typically examine differences between students who are and are not recorded as eligible for free or reduced-price lunch, an imprecise measure of family income. Only Grissom et al. (2019) use a more continuous student-level measure of socioeconomic status derived from the ECLS-K survey, including parental education, occupation, and income. However, this composite measure is aggregated into five quintiles and cannot speak directly to the relationship between income and GT identification as it combines multiple measures of SES. Understanding differences in gifted identification over the full distribution of family income is important for better understanding who does and does not have access to GT programs.

We contribute to this literature by using detailed family income data to document how GT identification varies across the entire distribution of family income. We show that these income gradients persist after accounting for between-school variation in GT identification and student test scores, and examine how they vary across grade, race/ethnicity, and sex.

Data

We use data from the Oregon Department of Education (ODE) on all Oregon public school students from 2009-2019, containing information about GT classifications, grade level, race/ethnicity, sex, and test scores. We link the ODE data with family income information from IRS tax records housed at the U.S. Census Bureau to create student-level family income percentiles (see the online supporting material for additional information, including demographic information and information about the distribution of family income).

Results

Figure 1 plots student family income on the x-axis and GT classification rates on the y-axis, controlling for student race/ethnicity, sex, grade level, and a linear trend in year.[1] The

[1] Because of the similarities between the conditional and unconditional means at each income percentile, we present conditional means throughout the paper.

“overall” estimates do not include school fixed effects, while the “within-school” estimates include school fixed effects, and thus can be interpreted as comparing students within the same school. We see that the likelihood that a student is GT increases sharply as family income rises. Students in the top percentile of family income have a 20.3% GT identification rate compared to a 3.2% GT identification rate for students in the bottom income percentile. The overlap between the “overall” and “within-school” results indicates that these differences emerge between students at the same school and are not simply driven by differences in students attending schools with larger or smaller GT programs. Nevertheless, the slight divergence between the overall and within-school estimates at the top of the income distribution indicates that the higher identification rates for high-income students is partly due to these students being more likely to attend schools with higher GT identification rates.

In supplementary analyses, we control for third grade achievement in both mathematics and English Language Arts and examine gifted identification rates for students in 4th through 12th grade. This effectively eliminates differences below the 80th percentile, suggesting that much of the gradient is related to differences observed in early standardized assessments. However, substantial advantages remain for the top income quintile, implying that identification advantages are above and beyond those related to achievement (see details in Online Supplement).

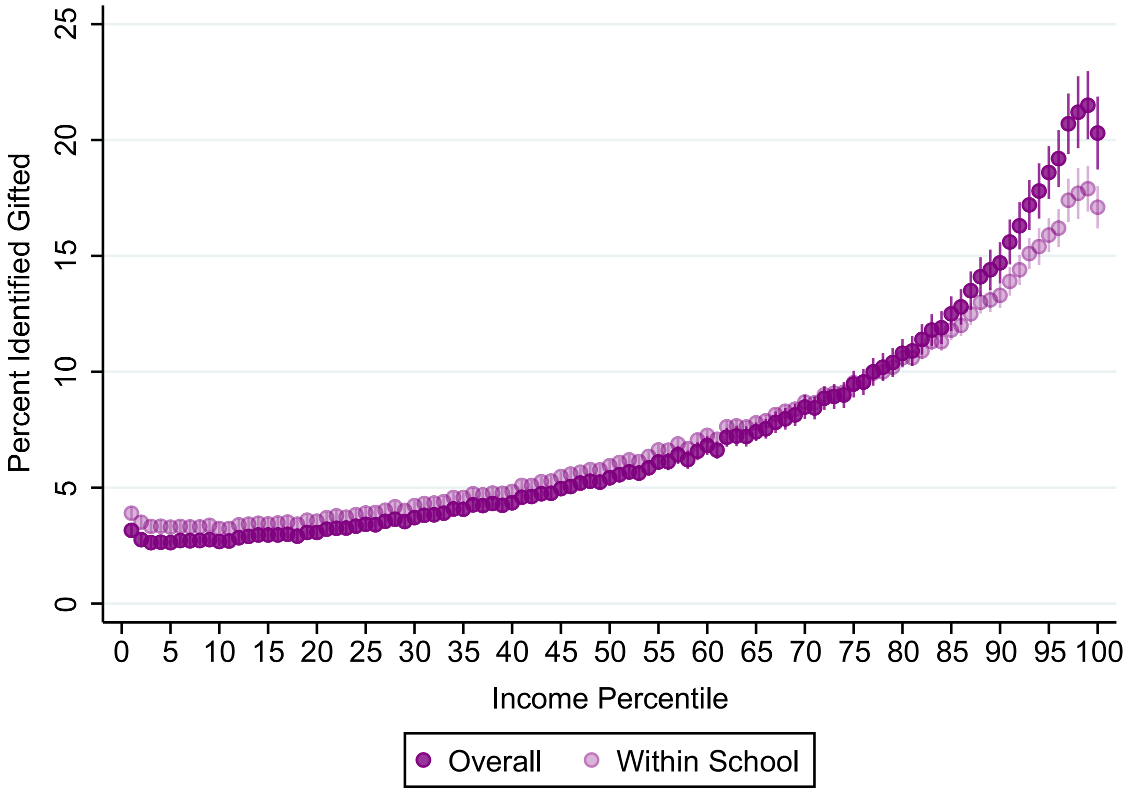
Figure 2 reports how the pattern in Figure 1 varies by grade level (2A), sex (2B), and race/ethnicity (2C). We see that the relationship between family income and GT identification is most pronounced in grades 6-8 and least pronounced in grades K-2 (2A), and that male and female students exhibit comparable patterns (2B). By contrast, there are stark differences by race/ethnicity, where Asian/Pacific Islander students have both the highest GT identification rates and the greatest variation between the bottom and top income percentiles. American Indian/Alaska Native and Hispanic students have the lowest GT identification rates and the smallest differences between the bottom and top income percentiles. Rates of GT identification for Black students are nearly identical to White students towards the bottom of the income distribution but diverge substantially at higher income levels, with higher income White students being 1.5 to 2 times more likely to be identified for GT compared to higher income Black students.

Conclusion

Using novel data, we document how the likelihood of GT identification varies across the distribution of family income. We find pronounced differences that persist even when comparing students in the same school and accounting for students' baseline test scores. The income gradient varies by race/ethnicity and is steepest in middle school. Taken together, our results highlight the ways that family income can be a barrier to GT identification for some students.

Figures

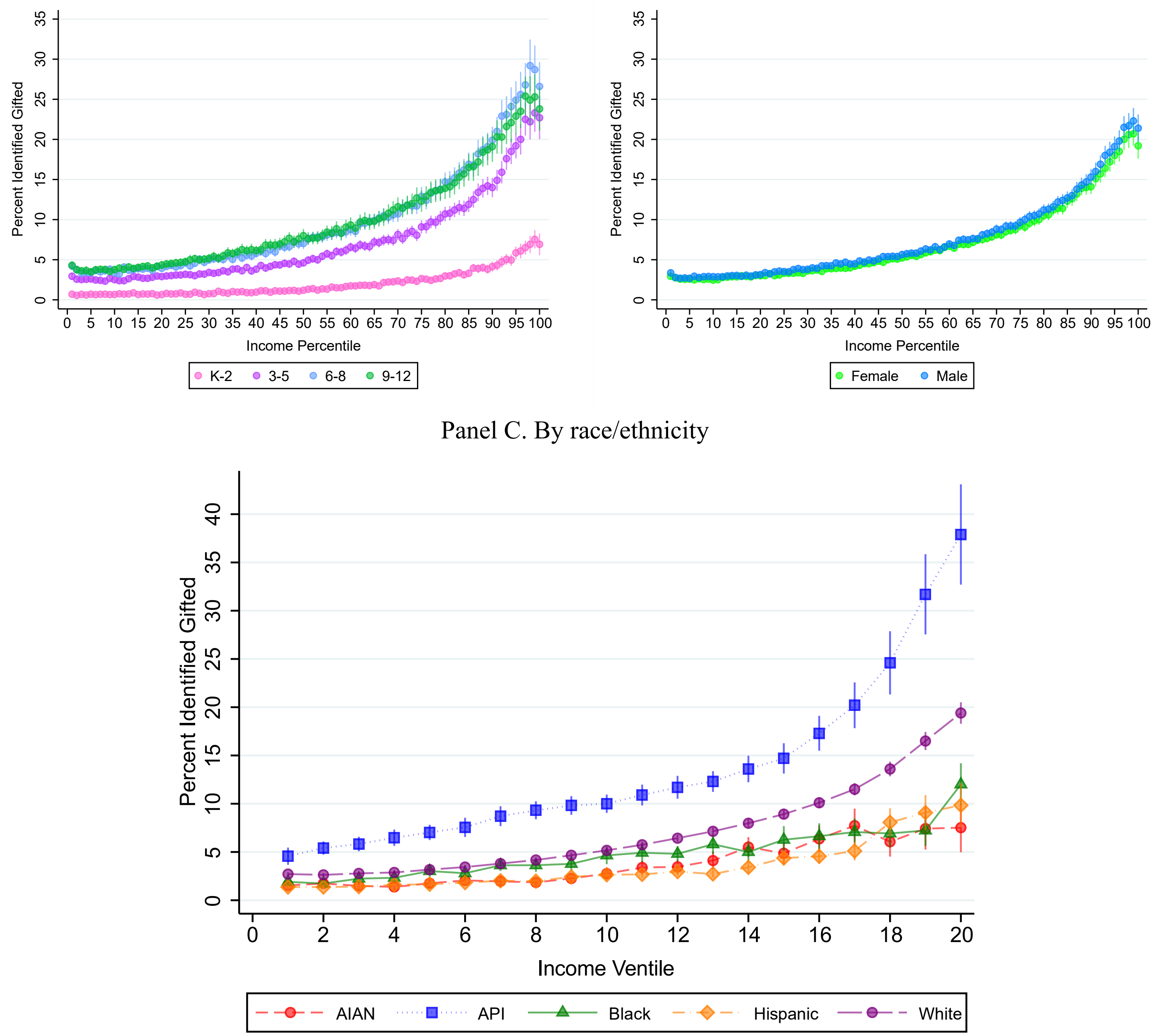
Fig. 1. Gifted identification rates for K-12 students by family income percentile



Notes. "Overall" identification rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, sex, grade, and a linear trend in year. "Within school" estimates come from models incorporating school fixed effects. DRB approval number: CBDRB-FY25-0309.

Fig. 2. Overall estimates of gifted identification by sex (A), grade (B), and race/ethnicity (C) by family income

Panel A. By grade Panel B. By sex



Notes. Identification rates are regression-adjusted means by income percentile (or ventile) estimated with models controlling for a linear trend in year. Panel A includes controls for sex and race/ethnicity. Panel B includes controls for grade and race/ethnicity. Panel C includes controls for grade and sex. Models are run separately by subgroup. Abbreviations are as follows: AIAN is American Indian/Alaska Native; API is Asian/Pacific Islander. DRB approval number: CBDRB-FY25-0309.

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Supporting Online Material

Table S1. Descriptive characteristics of Oregon public school students overall and by gifted status, 2009-2019

	Overall	**Not Gifted**	**Gifted**
Overall		0.930	0.070
Sex			
Female	0.486	0.488	0.469
Male	0.514	0.512	0.531
Race/Ethnicity			
American Indian/Alaska Native	0.016	0.017	0.006
Asian/Pacific Islander	0.047	0.043	0.101
Black/African American	0.025	0.026	0.012
Hispanic/Latine	0.077	0.081	0.023
Multiracial	0.048	0.047	0.057
White	0.787	0.786	0.801
Grade Level			
K-2	0.228	0.241	0.061
3-5	0.233	0.234	0.226
6-8	0.232	0.226	0.309
9-12	0.307	0.299	0.404
Availability of PIK and Income			
No PIK	0.038	0.040	0.014
PIK with no income	0.038	0.039	0.024
PIK and income	0.924	0.921	0.962
N	6,165,000	5,732,000	434,000

Notes. Table S1 presents characteristics of the population of Oregon public school students from the 2008-2009 to 2018-2019 school years. Cells report the proportion of the student population with each characteristic. All proportions and Ns are rounded according to Census rounding rules. Abbreviations are as follows: PIK is protected identification key.

Data

We use unique data that link records from the Oregon Department of Education (ODE) containing information about students' gifted classifications with IRS records containing information about students' family income (cf. Spiegel et al., 2025).[2] We restrict our analytic sample to K-12 students with non-missing demographic information (race/ethnicity, grade, and sex) enrolled in Oregon public schools from the 2008-2009 to 2018-2019 school years. Of these, we can link 5,671,800 student-year observations (92 percent) to family income information.

We link these records using protected identification keys (PIKs) that are assigned by the Census Bureau to both ODE and IRS records using the Person Identification Validation System.[3] We then locate student PIKs from the ODE data on the IRS Form 1040 records in which students are claimed as dependents and use the adjusted gross income (AGI) from the record as a measure of family income. We align school years to the tax filing year of the fall semester (e.g., family income for the 2018-2019 school year is measured using tax records for 2018). Because we are treating family income as a more stable characteristic of students and due to year-to-year variation in income that can create problems for characterizing educational disparities (Rothstein & Wozny, 2013), we use a five-year average of AGI. We adjust all AGI amounts to 2019 dollars. We are not able to assign 7.6 percent of students to a family income percentile for one of two reasons: they do not receive a PIK[4] (3.8 percent) or they receive a PIK but do not appear on tax records from 2004-2018 (3.8 percent; see Table S1).

[2] We use family income to refer to tax unit income.

[3] For more information on this process, see Wagner & Lane (2014).

[4] Broadly speaking, students might not be assigned a PIK due to missing or erroneous information in ODE administrative records for the student, or because they do not have a social security number, since data on individuals with social security numbers are used to build the reference file used to assign PIKs.

As family income tends to rise as students age, we calculate family income percentiles within birth cohort to avoid systematically categorizing older students as higher income.[5] Within each birth cohort and tax year, we rank students according to their family income and assign them to 100 approximately equal-sized ordered bins. This results in roughly 60,000 students assigned to each percentile, with the first percentile comprised of the students with the lowest family incomes,[6] and the 100th percentile comprised of students with the highest family incomes. Appendix Figure S1 shows the pseudo-median AGI for each income percentile.[7] The 100th income percentile has a pseudo-median AGI of $598,600. Key income cut-offs for poverty ($25,100), free lunch eligibility ($32,630), and reduced-price lunch eligibility ($46,435) for a family of four correspond to approximately the 21st, 30th, and 45th percentiles, respectively. For analyses by race/ethnicity, sample sizes for some student populations are too small to disclose at the percentile level, so we instead elect to report results by income ventiles (i.e., 20 equally sized groups).

Methods

We present model-based estimates that closely align with unadjusted classification rates to describe differences in the rates of identification for gifted education among students across the distribution of family income. Specifically, we estimate variations of the following model:

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[5] We define birth cohorts from September of one year through August of the next so that they would be equivalent to grade if all students started school at the same age and remained on-time for grade level.

[6] Although the first income percentile in our data reflects students with the lowest IRS-reported AGI, it is important to note that some families who are high-resource report low AGI due to capital losses. This makes the first percentile unique– it includes both very low-income families and families who claim large investment losses which bring their taxable income quite low (cf. Spiegel et al., 2025).

[7] To comply with Census disclosure standards, we cannot identify the exact median value, so instead we report the average income of observations within a narrow window of the true median.

$$Y_{icgt} = \sum_{p=2}^{100} \beta_p \cdot \mathbb{1}(\text{IncomePercentile}_{ict} = p) + \boldsymbol{X}_{\boldsymbol{i}}'\gamma + \delta \cdot t + \eta_g + \varepsilon_{icgt} \quad (1)$$

where Y_{icgt} is the outcome of interest for student i in birth cohort c, grade g, and year t; $\mathbb{1}(\text{IncomePercentile}_{ict} = p)$ is an indicator for income percentile p; $\boldsymbol{X}_{\boldsymbol{i}}'$ is a vector of individual-level covariates (race/ethnicity and sex); t is a continuous year variable capturing secular time trends; and η_g are grade fixed effects. Values of $\text{IncomePercentile}_{ict}$ are calculated within birth cohort c and year t. These income percentile indicators are fully saturated from $p = 2$ to 100, omitting percentile 1 as the reference group. Standard errors are adjusted for clustering at the school level. Using the estimated coefficients from this model, we calculate adjusted predictions for each income percentile p as:

$$\hat{\mu}(p) = \frac{1}{N} \sum_{i=1}^{N} \left[\hat{\beta}_p + X_i'\hat{\gamma} + \hat{\delta} \cdot t_i + \hat{\eta}_{g_i} \right] \quad (2)$$

where, for each individual i, we predict their outcome by setting their income percentile to p while keeping all other covariates at their observed values. We then average these individual predicted values across all N individuals in the sample. By doing so, the adjusted prediction $\hat{\mu}(p)$ reflects the average expected identification outcome if every student had income at percentile p while preserving the observed distribution of all other covariates in the sample. This provides a covariate-adjusted, population-average estimate of the outcome at each income percentile, which we plot with 95% confidence intervals.

For heterogeneity analyses, we estimate the models separately by subgroup (e.g., estimate the model separately for males and females). Due to small sample sizes for some racial/ethnic groups, we replace income percentiles with income ventiles (i.e., 20 equal groups) to produce estimates by race/ethnicity.

In addition to subgroup analyses, we also present overall estimates of gifted identification controlling for student achievement. We utilize end-of-year state summative assessments administered by ODE in English Language Arts and math as a measure of academic achievement, and standardize these test scores by subject, grade, and year using the full population of test takers. A mean index is then created by averaging across math and ELA for each student. We incorporate this mean achievement index as a control variable in model (1). Because receiving gifted services can impact student performance on standardized tests, controlling for contemporaneous test scores may bias estimates of the relationship between income and GT identification. Therefore, we elect to control for 3rd grade test scores and estimate model (1) for students in grades 4 through 12, excluding any gifted students identified in 3rd grade or earlier. While this restricts our sample of gifted students, 63.2% of gifted students are identified in 4th grade or later in Oregon, suggesting that we are still able to examine gifted identification dynamics for the majority of students receiving gifted services.

For each analysis (overall, with test score controls, and by subgroup) we present two sets of estimates. The first set are estimated using the model described above, which we call "overall" in each figure and plot using darkly shaded circles. For the second set of estimates, we add a school fixed effect to model (1) to remove variation in identification outcomes explained by between-school differences. This enables us to examine whether the variation we observe in identification by income is explained by the types of schools high- and low-income students attend or whether the relationships hold within schools. We call these models "within-school" in each figure and present them using lightly shaded circles. For the subgroup analyses by race/ethnicity, we present results from the "overall" and "within-school" in separate figures.

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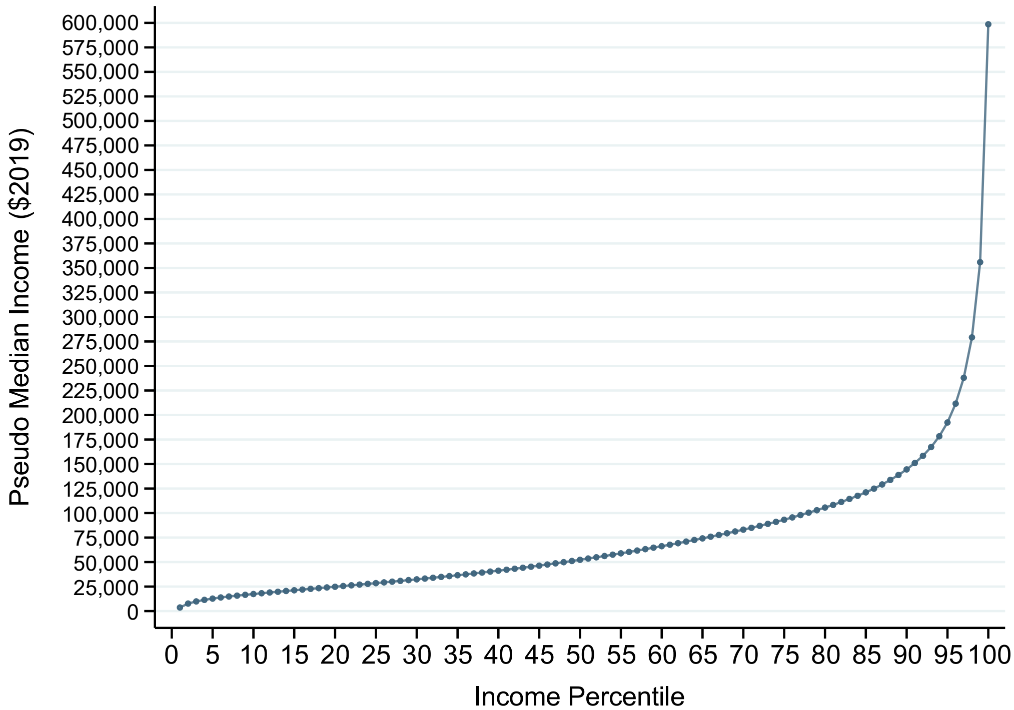
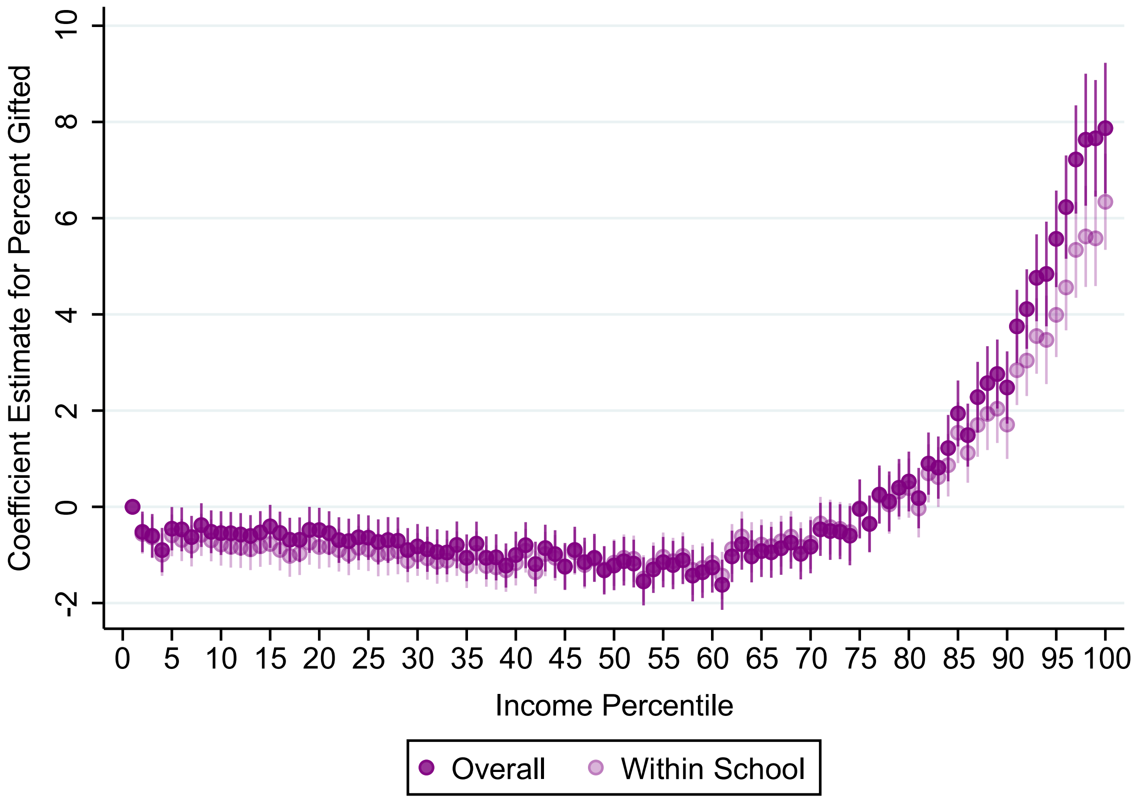
Fig. S1. Pseudo-median income in 2019 dollars by income percentile



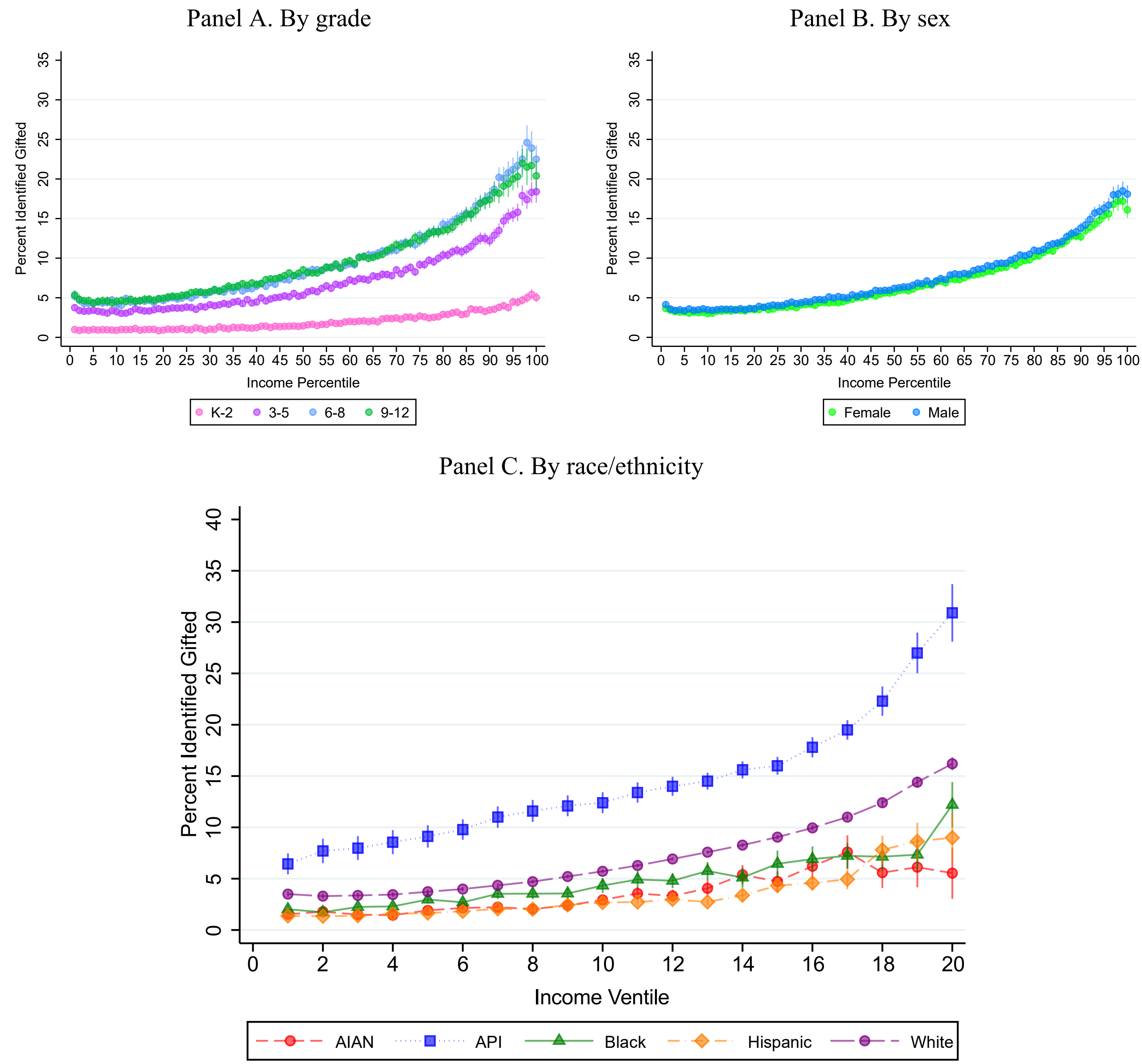
Notes. Pseudo-median income is calculated as the average income of observations within a narrow window of the true median income. DRB approval number: CBDRB-FY25-0309.

Fig. S2. Coefficients for gifted identification rates in grades 4-12 with grade 3 test score controls



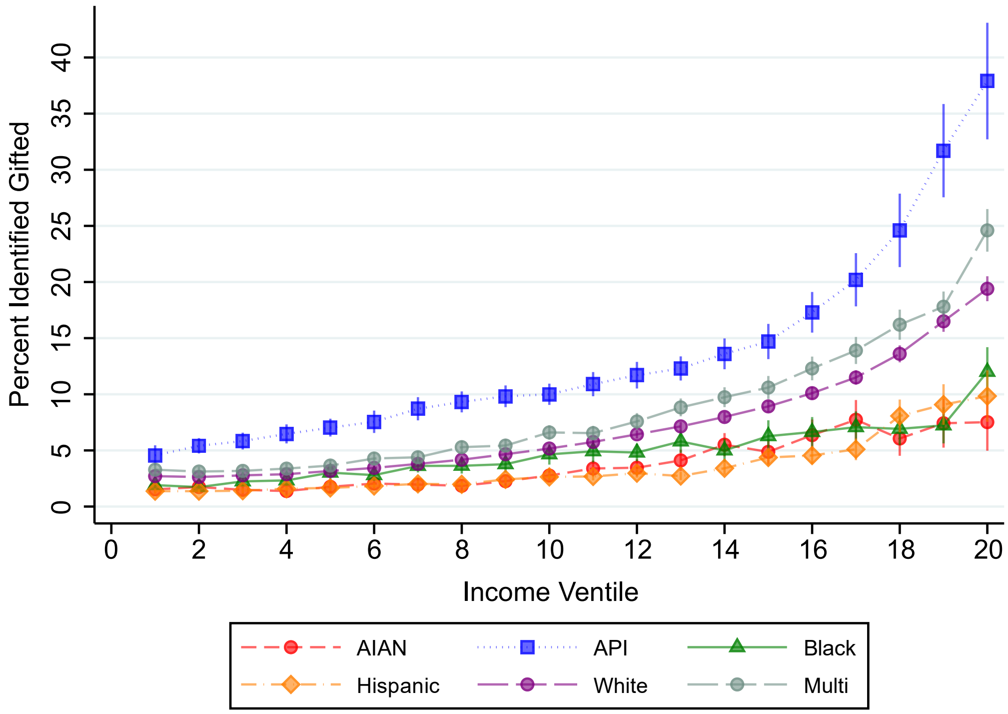
Notes. Fig. S2 reports coefficient estimates from models regressing gifted identification on income percentile and controls for a composite of standardized 3rd-grade math and ELA test scores among students in grades 4 through 12 who were not identified as gifted prior to 4th grade (63.2% of all gifted students). "Overall" identification models control for race/ethnicity, sex, and a linear trend in year. "Within school" models additionally incorporate school fixed effects into the "overall" models. DRB approval number: CBDRB-FY25-0309.

Fig. S3. Within-school estimates of gifted identification by sex (A), grade (B), and race/ethnicity (C) by family income



Notes. Identification rates are regression-adjusted means by income ventile estimated with models controlling for a linear trend in year and school fixed effects. Panel A includes controls for sex and race/ethnicity. Panel B includes controls for grade and race/ethnicity. Panel C includes controls for grade and sex. Models are run separately by subgroup. Abbreviations are as follows: AIAN is American Indian/Alaska Native; API is Asian/Pacific Islander. DRB approval number: CBDRB-FY25-0309.

Fig. S4. Estimates of gifted identification by race/ethnicity by family income ventile including Multiracial students



Notes. Identification rates are regression-adjusted means by income ventile estimated with models controlling for grade, sex, and a linear trend in year. Models are run separately by subgroup. Abbreviations are as follows: AIAN is American Indian/Alaska Native; API is Asian/Pacific Islander; Multi is multiracial. DRB approval number: CBDRB-FY25-0309.