



EdWorkingPaper No. 26-1374

School-Based Disability Identification Varies by Student Family Income

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VERSION: January 2026

Suggested citation: Ainsworth, Nicholas, Christopher Cleveland, Leah R. Clark, Jacob Hibel, Quentin Brummet, Andrew Saultz, Emily Penner, Michelle Spiegel, Paul Yoo, Juan Camilo Cristancho, Paul Hanselman, and Andrew Penner. (2026). School-Based Disability Identification Varies by Student Family Income. (EdWorkingPaper: 26-1374). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/dpwm-2673>

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CES 25-74

December 2025

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Abstract

Currently, 18 percent of K-12 students in the United States receive additional supports through the identification of a disability. Socioeconomic status is viewed as central to understanding who gets identified as having a disability, yet limited large-scale evidence examines how disability identification varies for students from different income backgrounds. Using unique data linking information on Oregon students and their family income, we document pronounced income-based differences in how students are categorized for two school-based disability supports: special education services and Section 504 plans. We find that a quarter of students in the lowest income percentile receive supports through special education, compared with less than seven percent of students in the top income percentile. This pattern may partially reflect differences in underlying disability-related needs caused by poverty. However, we find the opposite pattern for 504 plans, where students in the top income percentiles are two times more likely to receive 504 plan supports. We further document substantial variation in these income-based differences by disability category, by race/ethnicity, and by grade level. Together, these patterns suggest that disability-related needs alone cannot account for the income-based differences that we observe and highlight the complex ways that income shapes the school and family processes that lead to variability in disability classification and services.

* 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 or the Oregon Department of Education. 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.

A central question confronting contemporary education systems is how to best meet the instructional needs of all students. Indeed, providing equal educational opportunities hinges on how schools target and allocate resources to students (Jencks, 1988). For an increasing percentage of students in the United States, additional resources at school are provided through the identification of a disability. As of 2023, almost 9 million students with disabilities (18% of all K-12 public school students) receive additional supports, services, and accommodations in school at a cost of \$40 billion annually (Kaput & O’Neal Schiess, 2024). The majority of these students receive special education services as mandated by the 1975 Individuals with Disabilities Education Act (IDEA; 7.5 million students or 15%; Irwin et al., 2024), which provide them with individualized instruction from specialized staff in various settings. This includes aides to facilitate their participation in general education, instruction in special education classrooms, or services like speech therapy (Kaler et al., 2025). An additional 1.4 million students with disabilities receive learning supports via Section 504 of the 1973 Rehabilitation Act (3% of students; Zirkel & Gullo, 2024), which grants them access to accommodations such as extended time on tests within a general education classroom.¹

Although the incorporation of students with disabilities into the education system marks an important shift in the equitable provision of schooling in the U.S. (e.g., Aron & Loprest, 2012), the appropriateness of disability identification as a means for providing supports remains deeply contested. While identification for services affords students with disabilities and their families access to specific legal protections and supports, it can also subject them to new forms of discrimination and lowered educational expectations (Shifrer, 2013; Artiles et al., 2016; Rivera & Tilcsik, 2023). Accordingly, emerging evidence suggests the effects of special

¹ We provide a more detailed discussion of special education services, 504 plans, and the differences between these two types of support in the section on methods.

education services are not uniform; services benefit many students who receive them but may negatively impact some recipients (Morgan et al., 2010; Ballis & Heath, 2021, 2023; O'Hagan & Stiefel, 2025). Education policymakers and practitioners thus face dilemmas in trying to match students with the supports that they need to thrive while avoiding misclassifications that harm their learning and development. These classification concerns are further complicated by the well-documented race/ethnicity and sex differences in disability identification rates that interact to particularly disadvantage Black and Native American boys (National Research Council, 2002; Hibel et al., 2010; Fish, 2022), raising questions about whether disability identification reflects biases in educational institutions or differences in need resulting from structural inequalities (Skiba et al., 2005; Artiles et al., 2010; Morgan et al., 2015; Grindal et al., 2019; Elder et al., 2021; Fish et al., 2025).

In either case, family resources are seen as central to understanding educational disparities in disability outcomes, both as a factor explaining the observed sociodemographic differences in classification rates and as an important axis of inequality in disability identification in their own right (Artiles et al., 2010; King & Bearman, 2011; Halfon et al., 2012; Rauch & Lanphear, 2012; Morgan et al., 2015; Belkin & Hobbs, 2018; Goldstein & Patel, 2019; Grindal et al., 2019; Winter et al., 2020). Yet, because school administrative data systems rarely have reliable information about a student's socioeconomic status, and family income in particular, relatively little is known about how identification rates vary across the income distribution (Schifter et al., 2019), especially for students from families at the extremes of the income distribution and for different types of disability categories or supports. Understanding this potential variability is crucial for ensuring educational systems appropriately match students to the learning supports they need to succeed in school and beyond.

In this paper, we use a novel data linkage of K-12 administrative records for the population of students in the State of Oregon from 2009 to 2019 with family income information from IRS tax records housed at the U.S. Census Bureau to examine differences in student disability identification across the distribution of family income. We document how identification for different types of supports (i.e., special education and 504 plans) and different disability categories (e.g., specific learning disability or autism) vary across income levels, and how these income gradients vary by student grade and race/ethnicity. Our study contributes to ongoing conversations about appropriate disability classification by providing the first empirical evidence on the relationship between school-based disability identification and detailed family income using population-level data.

Results

Figure 1 plots student family income percentile on the x-axis and overall special education identification rates on the y-axis, controlling for student race/ethnicity, sex, grade level, and a linear trend in year.² This figure demonstrates that the rate of classification is nearly four times higher for students from families in the lowest income percentile than in the top income percentile (24.8% vs. 6.8%). To examine whether this pattern is driven by between-school differences in the rate of special education classification at the schools that high- and low-income students attend, Figure 1 also plots results from models that compare classification rates of students within the same school. The overlap between the two sets of estimates suggests that the income-based differences that we observe are replicated within schools and therefore do not simply reflect differences between the schools attended by high- and low-income students.

² Because of the similarities between the conditional and unconditional means at each income percentile, we present conditional means throughout the paper.

Panels A-F of Figure 2 reproduce the logic of Figure 1, presenting special education classification by income separately for each of the six most common disability types. Given the different prevalence rates of each disability classification, the y-axes vary across these panels. Across these figures, we see a similar pattern as in Figure 1, with low-income students being classified at higher rates than high-income students. The strength of this relationship, however, varies. For specific learning disabilities (SLD) students in the bottom percentile are almost six times more likely to be classified than those in the top (7.3% vs 1.3%), while for emotional behavior disabilities (EBD) they are ten times more likely (2.0% vs 0.2%). There are similarly large disparities for intellectual disabilities (ID; 1.9% vs. 0.3%; 6.3 times). However, this pattern is weaker for speech or language impairment (SLI; 4.6% vs 1.8%; 2.6 times) and other health impairments (OHI; 3.9% vs 1.1%; 3.5 times). For autism, the relationship is notably more muted. Although students at the bottom of the income distribution are about 2.5 times more likely to receive an autism classification than those in the top percentile (2.4% vs 1.0%), the relationship through the middle of the income distribution is almost entirely flat. Identification rates for students in the fifth to the seventieth percentile are nearly constant, hovering around 1.5%.

Figure 3 plots the rate at which students are classified as needing 504 plans under Section 504 of the Rehabilitation Act which, compared to special education services, have fewer procedural requirements and only provide students with accommodations, such as extended time on tests, as opposed to specialized instruction. In stark contrast to Figure 1, high-income students have higher rates of accommodations as part of a 504 plan. For example, students in the 95th percentile of the income distribution are twice as likely to have a 504 plan as students in the 5th percentile (2.9% vs. 1.5%). Further, in contrast to Figure 1, the divergence of the within-school differences from the overall rate at the top of the income distribution in Figure 3 indicates that

these income differences are partially driven by differences in the degree to which schools with more high-income students use 504 plans.

To better understand how the school experiences of high- and low-income children vary as they progress through school, we use a synthetic cohort approach to examine income-based classification by grade level. Figure 4A plots overall special education (Figure 1) rates separately for students in early elementary (K-2), late elementary (3-5), middle (6-8), and high school (9-12). We find evidence of strong income gradients in special education classification across all four grade groupings, with starker patterns in middle and high school and less pronounced differences in early elementary school. In the top income quartile, students' special education classification rates are relatively low in K-2, peak in grades 3-5, then decline in middle and high school. At the very top of the income distribution, we observe that middle school students have low special education rates similar to early elementary students and that high schoolers have even lower rates. Indeed, identification rates at the top of the distribution drop by 40 percent between their peak in grades 3-5 and high school, suggesting that reclassification is relatively common among high-income students.

This pattern contrasts markedly with the bottom of the distribution, where the reclassification of students to general education appears to happen later and for fewer students. In the bottom quartile, we again see a relatively low rate of special education classification in early elementary school and that classification rates increase in later elementary school. However, this peak is longer lasting, as special education classification rates do not decline appreciably in middle school and only do so in high school. Additionally, these high school declines are relatively minor, decreasing only 10 percent compared with their peak in late elementary school for students at the bottom of the income distribution.

Panel B of Figure 4 plots rates of 504 plan receipt by grade band across the income distribution. Like special education, disparities between high- and low-income students are largest in middle and high school, but the direction of the relationship is reversed. In early elementary school, 504 plan receipt is nearly flat across the income distribution, although only a small percentage of students receive this type of support. The income gradient favoring high-income students emerges in late elementary school and grows through high school. By grades 9-12, high-income students are the most likely of any student group to receive a 504 plan, with students in the 95th percentile being more than twice as likely as those in the 5th percentile to have a 504 plan (4.5% vs. 2.0%).

Although these analyses convey important heterogeneity by disability support (special education vs. 504 plan), disability type, and grade, they mask differences by other meaningful sociodemographic characteristics. Figure 5A plots special education identification rates by race/ethnicity and income. Heterogeneity by sex is reported in the Supporting Information. Because of small sample sizes for income percentiles, we use ventiles of family income for analyses by race/ethnicity. Consistent with prior work (National Research Council, 2002; Fish, 2022), we find that American Indian/Alaska Native and Black students are more likely to be identified for special education compared with White students and show that this is the case across the income distribution. Notably, differences in identification rates for Black and White students vary across the income distribution. In the bottom half of the distribution, low-income Black students are 1 to 2 percentage points more likely than White students to be identified for special education. However, unlike White students, identification rates for Black students start to decline more slowly starting in the middle of the income distribution. As a result, the disparity

between Black and White students from the middle to the top of the income distribution ranges from 4 to 7.5 percentage points.

Special education identification differs for Hispanic and Asian/Pacific Islander students. Across most of the income distribution, Hispanic students are several percentage points less likely to be identified for special education than White students. However, towards the top quarter of the distribution Hispanic students surpass White students in identification rates. Asian/Pacific Islander students, by contrast, are a clear outlier compared to all other racial/ethnic groups. Their special education rates across the income distribution are nearly flat at around 9%, declining somewhat at the top. Asian/Pacific Islander students in the bottom income ventile are therefore less likely to be identified for special education services than even the highest income Black, Hispanic, and American Indian/Alaska Native students.

Panel B of Figure 5 examines identification outcomes by income and race/ethnicity for 504 plans. In contrast to special education, White students in the bottom income ventile are the most likely (along with Multiracial students; *SI Appendix*, Figure S5) to receive a 504 plan compared to other student groups. Estimates for students from other racial/ethnic backgrounds are somewhat noisier given small sample sizes at each income ventile. Nevertheless, rates of 504 plan receipt among Hispanic and Asian/Pacific Islander students are substantially lower than those of White students throughout the income distribution, though rates for Hispanic students nearly converge at the top ventile. For Black students, the opposite pattern from special education identification (Figure 5A) emerges: disparities between White and Black students in 504 plan receipt are largest throughout the bottom of the income distribution and converge towards the top of the distribution.

Discussion

In providing the first analysis of school-based disability identification using population-level data with detailed measures of family income, we document substantial variation across the income distribution, particularly for students at the top and bottom of the distribution. We show that students from high-income backgrounds are less likely to receive special education services than their lower-income peers, but more likely to receive accommodations through 504 plans. These different classification pathways are not simply a function of the schools that low- and high-income students attend, as we document that these patterns also exist between students attending the same school, raising questions about the causes of the observed differences in disability identification for students from different income backgrounds.

Disability identification results from a confluence of factors related both to students' needs, such as lower academic achievement or greater behavioral challenges, and to the labeling of those needs as a condition requiring additional support (Fish, 2022). Given that poverty can negatively impact child health and development (Aber et al., 1997; Rauch & Lanphear, 2012; National Academies of Sciences, 2019; Currie & Goodman, 2020), it seems unlikely that students across the income distribution have the same disability prevalence and thus disability-related needs for support at school. Nevertheless, if differences in needs caused by poverty explained the differences in identification we observe across the income distribution, we might expect to see that low-income students always receive greater levels of support. The stark divergence between the classification rates for special education services and 504 plans across the income distribution suggests that our findings are unlikely to simply reflect differences in students' underlying needs. Rather, the divergence in these income-based differences appears to

reflect different understandings of these programs and how families and schools negotiate supporting the needs of students with different income backgrounds.

These different understandings of how to support students are underscored by the substantial variation we observe in the relationship between income and disability identification across disability categories, grade levels, and racial/ethnic groups. We find that income is more strongly related to classification for some disability categories than others. In particular, the largest income disparities in identification are for special education categories like emotional behavior disabilities and intellectual disabilities that scholars characterize as carrying higher degrees of social stigma among teachers and families. By contrast, “higher status” disabilities like autism and speech or language impairment, which typically involve placements in more inclusive settings or access to desirable special education services, have the smallest income-based disparities (cf. Fish, 2019).

We also find evidence that high- and low-income students have very different trajectories as they progress through school. Special education rates for high-income families peak in late elementary school and then fall as students move into middle and high school. It appears that high-income students are accessing services early, when interventions are widely perceived to be beneficial (e.g., National Research Council, 2002) and are being reclassified out of special education in the secondary grades, a time during which a disability label is perceived as particularly stigmatizing (Shifrer, 2013). Conversely, special education rates for low-income students do not drop in middle school and only modestly decline in high school, suggesting that once low-income students are classified for special education this label is more likely to stay with them throughout their educational careers. The opposite pattern emerges for 504 plans. Rates of identification are low in grades K-2 and increase from late elementary school through

high school for all students. Yet, identification rates increase more steeply for high-income students, making them the group most likely to receive 504 plan accommodations in high school, a period that coincides with students' exposure to consequential high-stakes testing requirements for college admissions (Belkin & Hobbs, 2018; Goldstein & Patel, 2019).

Finally, we show that income-based differences in identification exist across all racial/ethnic groups but vary in important ways. The income gradients for special education identification are less steep for Hispanic, Black, and especially Asian/Pacific Islander students. Black students are only slightly more likely than White students to be identified for special education services at the bottom end of the income distribution, but substantially more likely towards the top end of the distribution. The opposite is true for 504 plans, where low-income Black students are less likely than White students to receive 504 plans but nearly as likely to receive them at high levels of income. By contrast, low-income Hispanic students are less likely than White students to receive either special education services or 504 plans and Asian/Pacific Islander students of all incomes are substantially less likely to be identified for either type of disability support compared to all other racial/ethnic groups. Explanations based on student needs cannot readily explain the markedly different income gradients we observe for students from different racial/ethnic backgrounds.

In documenting these income-based differences in special education and 504 plan receipt, our results highlight the insufficiency of accounts that understand disparities in special education and 504 plan identification solely in terms of students' disability-related needs (cf. Grindal et al., 2019). Instead, our results underscore how schools and families understand who needs special education and 504 plan supports. It seems likely that at least some of these differences reflect biases in the identification process or efforts by high-income parents to secure advantages for

their children. Although disability identification is based on diagnostic criteria, the process is infused with a degree of subjectivity, particularly for the types of disabilities or supports that involve clinical or practitioner judgment like learning or emotional behavior disabilities (National Research Council, 2002). Teachers and school staff perceive student exceptionality differently based on a student's background (Fish, 2017, 2022). Parents also play a key role in shaping categorizations, strategically obtaining advantageous classifications and supports for their children while helping them avoid stigmatizing labels or potentially harmful services (Horvat et al., 2003; Ong-Dean, 2009; King et al., 2014; Cowhy et al., 2024).³

This study cannot adjudicate the optimal rate of special education and 504 plan receipt, nor can it address the degree to which the differences in classification represent differences in students' need for support or biases embedded in the identification process. Nonetheless, these findings clearly indicate that students from high- and low-income families receive very different supports even within the same school, and suggest that either low-income students, high-income students, or both are not being classified on disability-related needs alone. Educators and policymakers concerned with ensuring that all students have the opportunities they need to thrive would do well to understand the processes that yield such divergent educational classifications.

Methods⁴

We use novel data that link records from the Oregon Department of Education (ODE) containing information about students' disability classifications with IRS records containing

³ For their part, schools also use disability identification strategically (Cullen, 2003; Dhuey & Lipscomb, 2011; Figlio & Getzler, 2006) and may leverage special education categorization as one mechanism to target additional resources to low-income students whose needs are not otherwise being met given existing resource constraints. Because 504 plans provide accommodations and are not accompanied by additional financial or instructional resources (Lewis & Muñiz, 2023), schools may conceptualize them as a support for students who do not require an additional investment of resources.

⁴ The analyses presented here use many of the same data elements and sources that Spiegel et al. (2025) used to examine classroom-level income segregation. Given the overlapping data and authorship team, our discussion of the methods overlaps with Spiegel et al. (2025).

information about students' family income (cf. Spiegel et al., 2025).⁵ 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. We can link 5,671,800 student-year observations (92 percent) to family income information.

We link these records using protected identification keys (PIKs) assigned by the Census Bureau to ODE and IRS records using the Person Identification Validation System.⁶ 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 treat 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 (3.8 percent) or they receive a PIK but do not appear on tax records from 2004-2018 (3.8 percent; see *SI Appendix*, Table S1).⁷ We discuss the implications of missing data in the Supporting Information (*SI Appendix*).

As family income tends to rise as students age, we calculate family income percentiles within birth cohorts to avoid systematically categorizing older students as higher income.⁸

⁵ We use family income to refer to tax unit income.

⁶ For more information on this process, see Wagner & Lane (2014).

⁷ 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.

⁸ 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.

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 being assigned to each percentile, with the first percentile comprised of the students with the lowest family incomes,⁹ and the 100th percentile comprised of students with the highest family incomes. Appendix Figure S1 shows the pseudo-median AGI for each income percentile.¹⁰ 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 (Child Nutrition Programs, 2018). 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).

Special Education and 504 plans. To examine disparities in disability classifications, we use data from the Oregon Department of Education, which collects information about student receipt of special education services and 504 plans. Schools are federally required to provide both types of supports (special education services and 504 plans) to qualifying students with disabilities (Bateman et al., 2020). Although a student with a disability may receive both special education services and a 504 plan, most students receive one or the other.¹¹ Special education services and 504 plans differ in that special education services have more formalized requirements and may provide students with a variety of services, including specialized

⁹ 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).

¹⁰ 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.

¹¹ In our sample, only about 0.1% of the total student population are students who have special education services and a 504 plan, which represents 0.7% of students receiving special education or 5.5% of students with 504 plans.

instruction from special education staff members (including in settings outside of the general education classroom), modifications of the curriculum, and accommodations such as preferential seating (Aron & Loprest, 2012). Special education also comes with funding through federal IDEA grants and other state and local contributions (Kolbe, 2021; Kolbe et al., 2023). By contrast, 504 plans have much less rigid procedural requirements and only provide students with accommodations, such as extended time on tests (Bateman et al., 2020). Schools do not typically receive funding for providing 504 plans (Lewis & Muñiz, 2023).

To qualify for either service, teachers typically refer students to school psychologists for testing to see if special education and/or 504 plan supports are warranted. In some cases, parents initiate this process. In addition to testing conducted by school psychologists, families can also have testing conducted by professionals outside of the school (National Research Council, 2002; Dragoo, 2019). To qualify for special education, a child must be found eligible under one of 13 federally recognized disability categories and demonstrate a need for special education or related services (Dragoo, 2019). For 504 plans, students may qualify under a wide range of disabilities so long as they substantially impact a major life activity and can be reasonably accommodated (Bateman et al., 2020).¹² Based on differences in the eligibility criteria and types of supports provided, 504 plans are typically provided to students who require less intensive supports. In contrast, special education serves a more diverse population of students with disabilities, including those with more complex needs.

In Table S1 we provide demographic information on the sample of Oregon public school students who receive special education services, 504 plans, or who do not receive either type of

¹² Section 504 plans may also be provided to students on a temporary basis or for a short duration of time. For example, a child may receive a time bound 504 plan as they are recovering from an illness or some other condition.

support. Our Supporting Information also includes demographic information for the six largest school-identified disability categories.

Empirical Approach. We present model-based estimates that closely align with unadjusted classification rates to describe differences in the rates of identification for special education services and 504 plans among students across the distribution of family income. Specifically, we estimate variations of the following model:

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

where Y_{icgt} is the outcome of interest indexed for student i in birth cohort c , grade g , and year t ; $\mathbb{1}(\cdot)$ is an indicator for income percentile p ; \mathbf{X}'_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. $\text{IncomePercentile}_{ict}$ 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:

$$\hat{\mu}(p) = \frac{1}{N} \sum_{i=1}^N [\hat{\beta}_p + \mathbf{X}'_i \hat{\gamma} + \hat{\delta} \cdot t_i + \hat{\eta}_{g_i}]$$

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.

We repeat this estimation procedure for each outcome, namely special education receipt (overall and by disability category) and 504 plan receipt. For heterogeneity analyses, we estimate the models separately by subgroup (e.g., estimate the model separately for males and females). For estimates by race/ethnicity, we replace income percentiles with income ventiles in the models.

For each outcome 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 only from the “overall” model but provide the “within school” estimates in the supporting information (*SI Appendix, Figure S6*).

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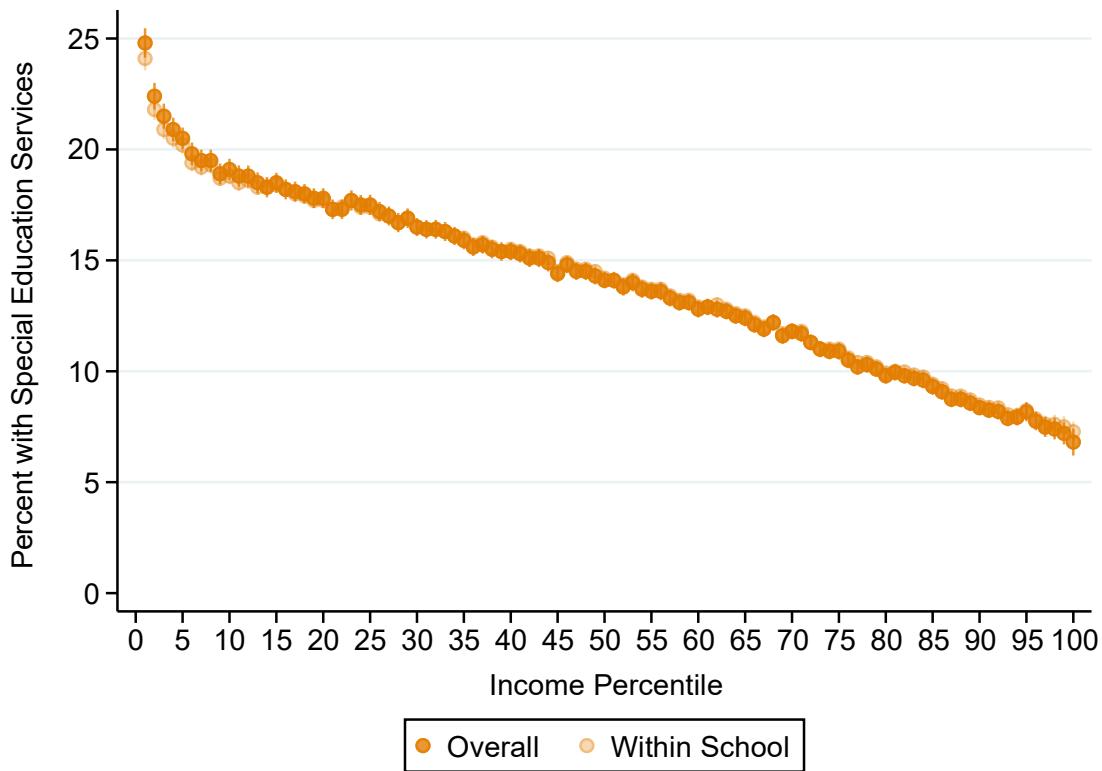
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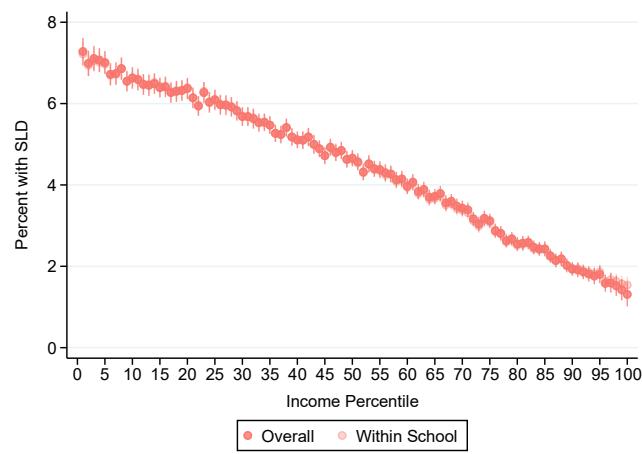
Fig. 1. Special education identification by income percentile



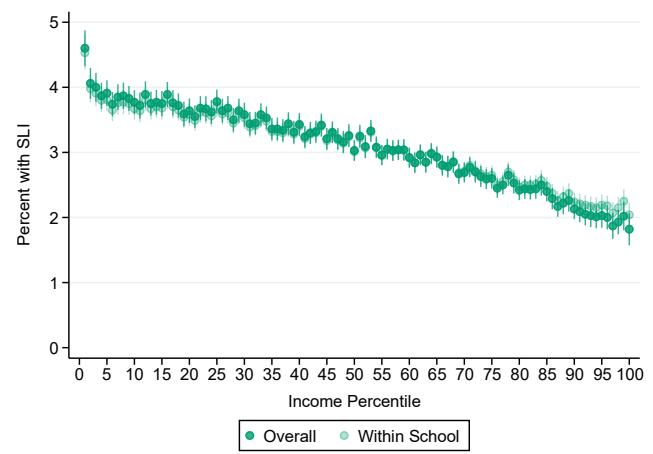
Notes. “Overall” identification rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, sex, grade, and a linear trend in year. “Within school” estimates come from models incorporating school fixed effects. DRB approval number: CBDRB-FY25-0309.

Fig. 2. Special education identification by disability category (A-F) by income percentile

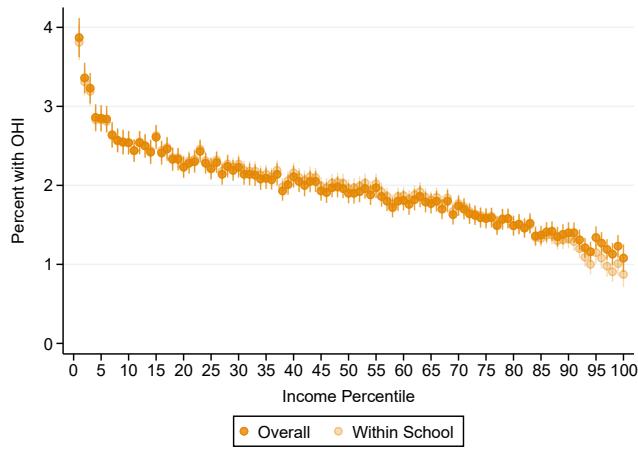
Panel A. Specific learning disability



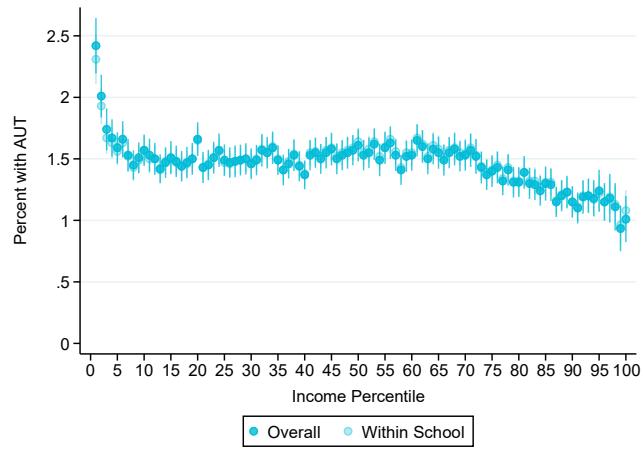
Panel B. Speech or language impairment



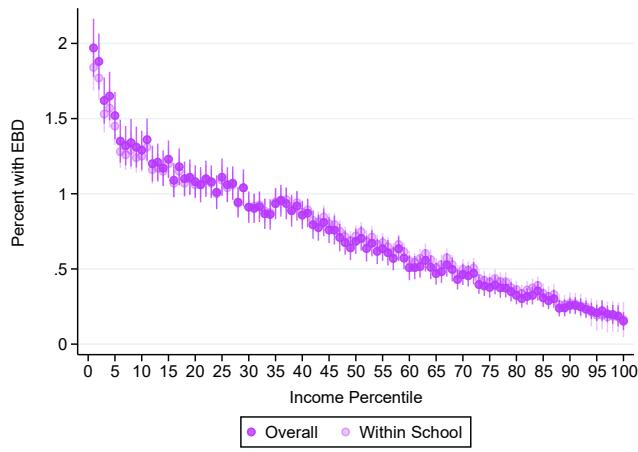
Panel C. Other health impairment



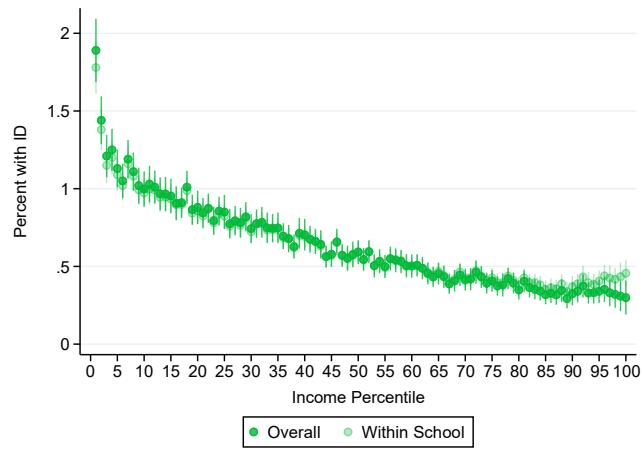
Panel D. Autism



Panel E. Emotional behavior disability

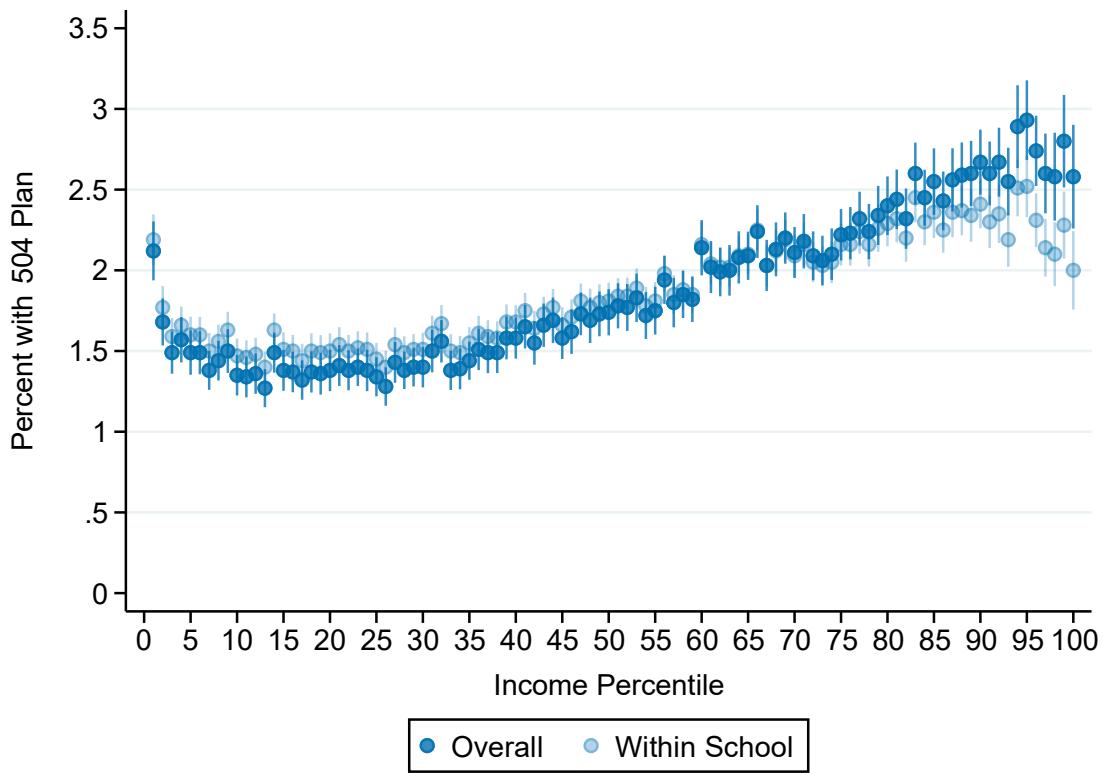


Panel F. Intellectual disability



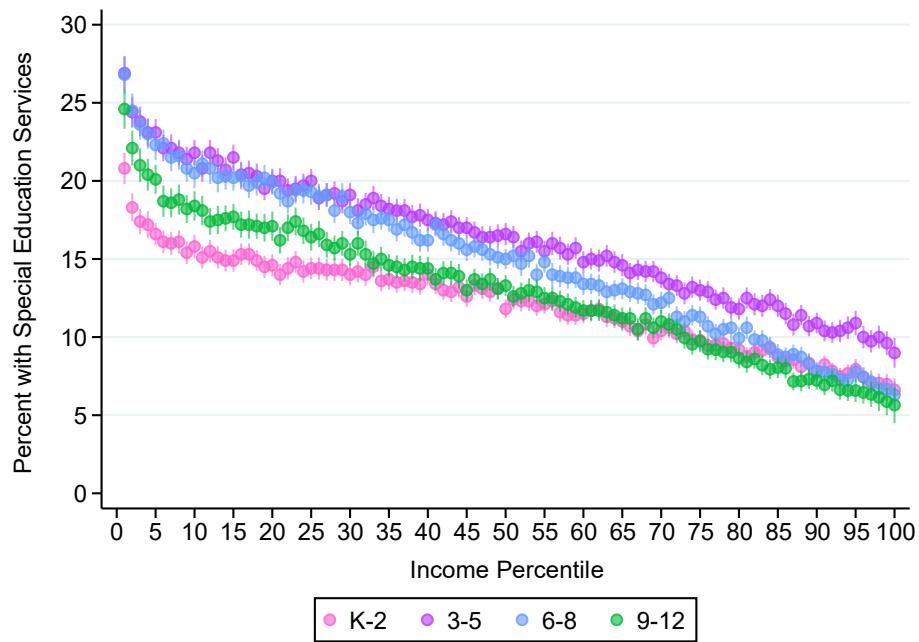
Notes. “Overall” identification rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, sex, grade, and a linear trend in year. “Within school” estimates come from models incorporating school fixed effects. DRB approval number: CBDRB-FY25-0309.

Fig. 2. Section 504 plan receipt by income percentile

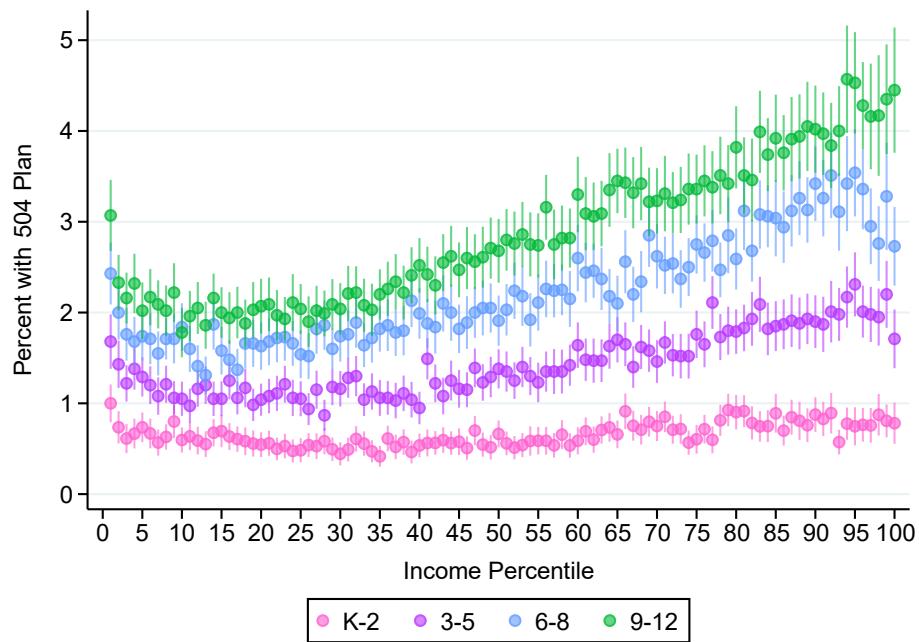


Notes. “Overall” identification rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, sex, grade, and a linear trend in year. “Within school” estimates come from models incorporating school fixed effects. DRB approval number: CBDRB-FY25-0309.

Fig. 3. Special education (A) and 504 plan (B) receipt by grade level and income percentile
 Panel A. Special education

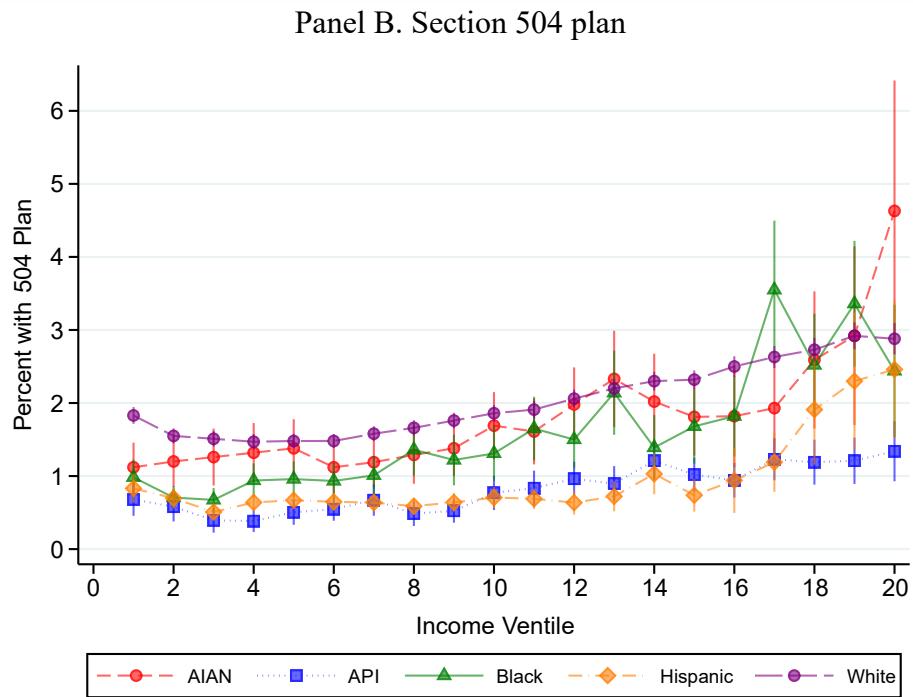
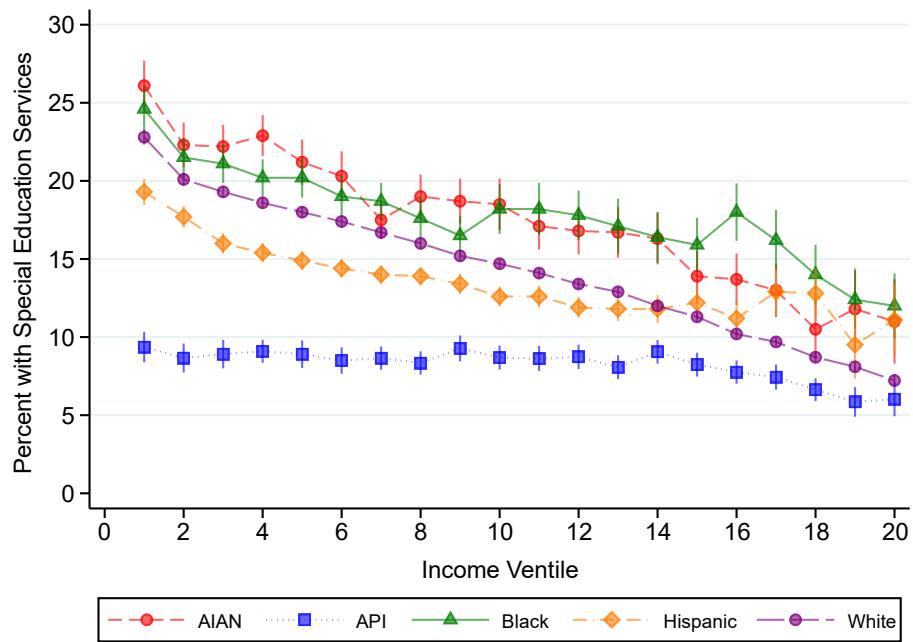


Panel B. Section 504 plan



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

Fig. 4. Special education (A) and 504 plan (B) receipt by race/ethnicity and income ventile
 Panel A. Special education



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

Supporting Information Appendix

Supporting Text

Heterogeneity by sex. In Figure S2 we plot special education and 504 plan receipt rates by sex. In absolute terms, the income gradient for special education identification is steeper among male students, ranging from 30.7% in the 1st percentile to 8.9% in the 100th percentile (a 21.8 percentage point difference). In comparison, female students range from 4.6% to 18.5% (a 13.9 percentage point difference). In relative terms, however, the gradient among female students is larger, as students in the bottom percentile are 4 times more likely to receive special education services (18.5% vs. 4.6%), while the relative difference among male students is 3.4 times (30.7% vs. 8.9%). Comparing male and female students, we find that across the income distribution, males are 1.5 to 2 times more likely than females to receive special education services. To put these differences by sex in perspective, we find that a male student in the top percentile of the income distribution (median income of \$598,600) is as likely to receive special education services (8.9%) as a female student in the 57th percentile (8.9%; median income of \$61,740).

We find less pronounced differences by sex for 504 plans. Male students are 1.4 times more likely than female students to receive 504 plans across the income distribution. While the absolute difference between the top and bottom of the income distribution is larger for male students, the relative difference is approximately equal. For both groups, students in the 95th percentile are about 2 times more likely to have a 504 plan than students in the 5th percentile (3.4% vs. 1.7% for males; 2.4% vs. 1.3% for females).

Missing data. In our analyses, we treat income as missing-at-random. In execution, this assumption means that when we calculate the special education and 504 plan rates in each income percentile, the denominator count reflects the number of students for whom we observe

income, not the total number of students in the state's public schools. An alternative would be to assume that missing income is equal to zero income, but we believe the missing-at-random assumption is more empirically plausible and less naive for multiple reasons. First, results from Clark & Bhaskar (2025) show that the missing income is equal to zero assumption is empirically implausible (Clark & Bhaskar, 2025). In a paper using similar data, we also find that school economic disadvantage rates derived from IRS data are virtually equivalent to those that supplement IRS data with program participation data, suggesting that students within a school with missing IRS data are similarly low-income to their school peers (Spiegel et al., 2024). Finally, assuming that missing income is zero income would be particularly analytically naive in our case because it would mean assigning the lowest 8 income percentiles to individuals for whom we lack income data, obscuring the reality for very low-income students.

Oregon as a case study. Although we analyze just one state, our findings from Oregon may provide insights into special education and 504 plan supports in other states (see *SI Appendix* Figs. S1-S3 in Spiegel et al. 2025 for state comparisons). Compared to the rest of the U.S., Oregon has similar rates of special education identification (15% in Oregon versus 15% nationally; Irwin et al., 2024) and 504 plan receipt (3% in Oregon versus 3% nationally; Zirkel & Gullo, 2024). To help situate Oregon in the broader national context, below we provide additional information regarding how Oregon compares to the other 49 states and the District of Columbia on several dimensions (all data are from 2017; cf. Spiegel et al. 2025):

- 1) Oregon ranked 38th in overall income inequality (as measured by the GINI index), with a GINI of .459; the GINI for the U.S. as a whole was .482.
- 2) Oregon ranked 25th in median income, with a median income of \$73,202, compared to a national median income of \$60,366.

- 3) Oregon's K-12 public school students were 63 percent White, 23 percent Hispanic, 2 percent Black, and 4 percent Asian. Nationally, 51 percent of public school students were White, 25 percent were Hispanic, 14 percent were Black, and 5 percent were Asian.
- 4) Oregon ranked 31st in the percent of public school students who attended charter schools, with 5.7 percent, compared to 6.0 percent nationally.
- 5) Oregon is one of 36 states that does not have a voucher program to allow children to attend private schools with public dollars.
- 6) Oregon, like 43 other states, allowed for inter-district enrollment.
- 7) Oregon ranks 30th in the percent of K-12 students who attend public schools.

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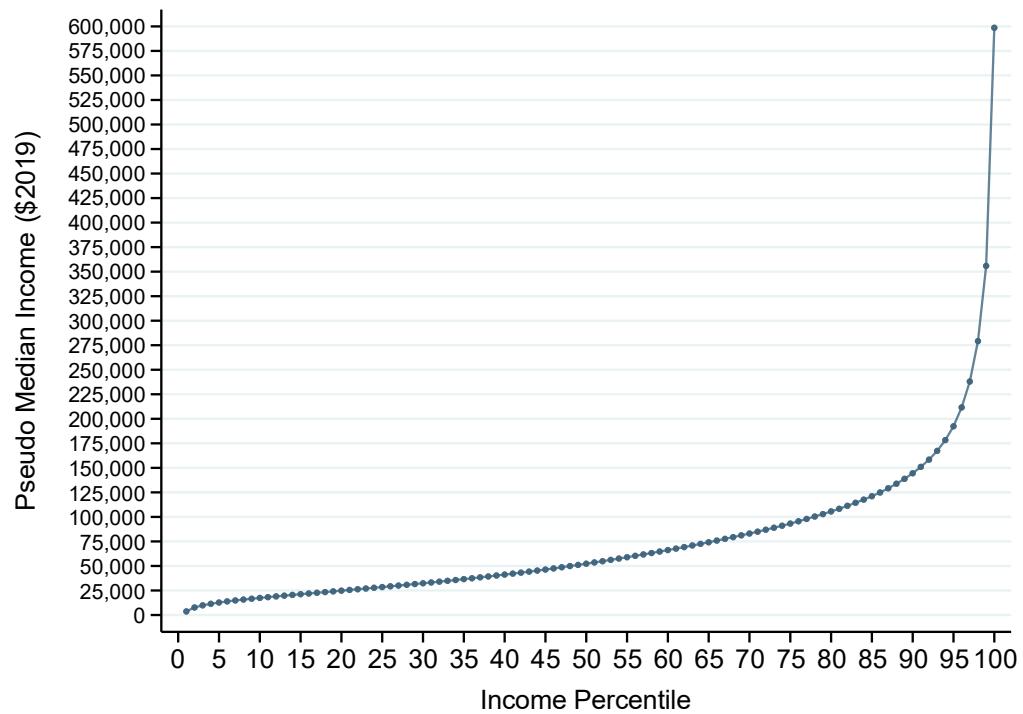
Tables and Figures

Table S1. Descriptive characteristics of Oregon public school students overall, by disability service, and by disability type, 2009-2019

	Overall	No SPED or 504								
		Plan	504 Plan	SPED	SLD	SLI	OHI	AUT	EBD	ID
Overall		0.841	0.018	0.142	0.045	0.031	0.020	0.015	0.008	0.007
<i>Sex</i>										
Female	0.486	0.513	0.411	0.338	0.399	0.339	0.287	0.161	0.249	0.445
Male	0.514	0.487	0.589	0.662	0.601	0.661	0.713	0.839	0.751	0.555
<i>Race/Ethnicity</i>										
American Indian/Alaska Native	0.016	0.015	0.013	0.022	0.025	0.021	0.023	0.015	0.024	0.026
Asian/Pacific Islander	0.047	0.051	0.022	0.025	0.016	0.036	0.016	0.044	0.011	0.028
Black	0.025	0.024	0.017	0.034	0.033	0.028	0.043	0.022	0.057	0.043
Hispanic	0.077	0.078	0.028	0.076	0.105	0.088	0.040	0.034	0.034	0.083
Multiracial	0.048	0.047	0.058	0.049	0.043	0.047	0.057	0.052	0.062	0.040
White	0.787	0.785	0.862	0.794	0.778	0.780	0.821	0.833	0.812	0.780
<i>Grade Level</i>										
K-2	0.228	0.236	0.080	0.198	0.027	0.478	0.106	0.207	0.093	0.089
3-5	0.233	0.228	0.178	0.269	0.248	0.345	0.246	0.240	0.229	0.187
6-8	0.232	0.229	0.275	0.247	0.340	0.121	0.290	0.238	0.286	0.239
9-12	0.307	0.307	0.467	0.286	0.385	0.056	0.358	0.315	0.392	0.485
<i>Availability of PIK and Income</i>										
No PIK	0.038	0.038	0.022	0.040	0.040	0.051	0.035	0.024	0.041	0.043
PIK with No Income	0.038	0.036	0.033	0.050	0.050	0.036	0.049	0.047	0.070	0.095
PIK and Income	0.924	0.926	0.945	0.910	0.910	0.913	0.916	0.929	0.889	0.862
N	6,165,000	5,185,000	111,000	878,000	278,000	192,000	122,000	90,000	48,000	42,000

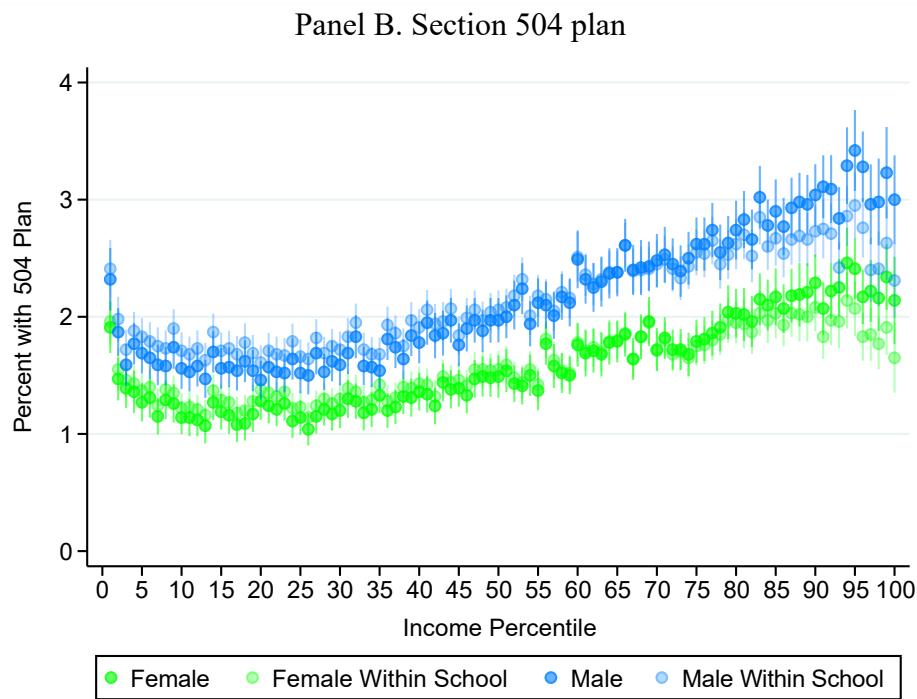
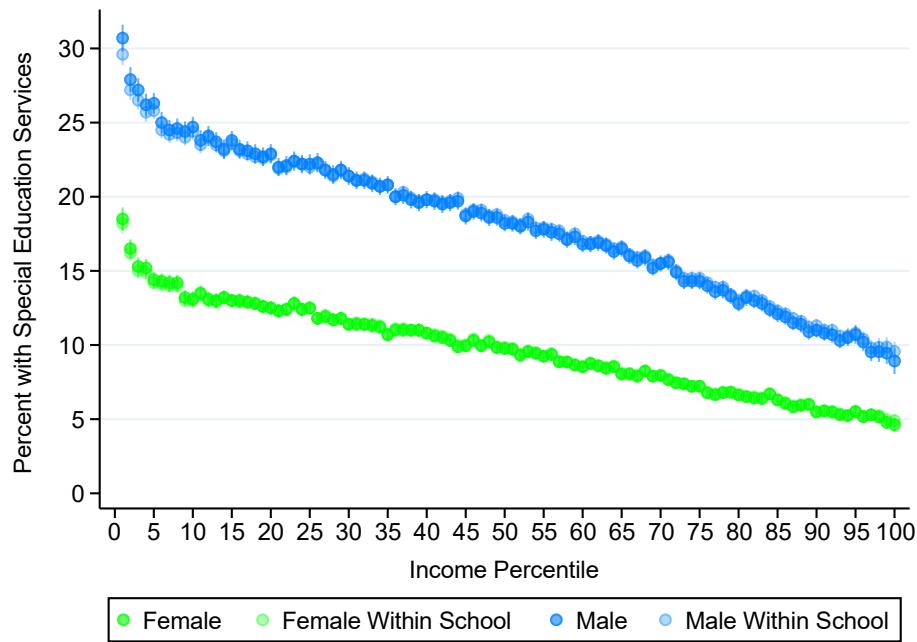
Notes. Table S1 presents characteristics of the population of Oregon public school students from the 2008-2009 to 2018-2019 school years. Cells present the proportion of the student population with each characteristic. All proportions and Ns are rounded according to Census rounding rules. Abbreviations are as follows: SPED is special education; SLD is specific learning disability; SLI is speech or language impairment; OHI is other health impairment; AUT is autism; EBD is emotional behavior disability; ID is intellectual disability; PIK is protected identification key.

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



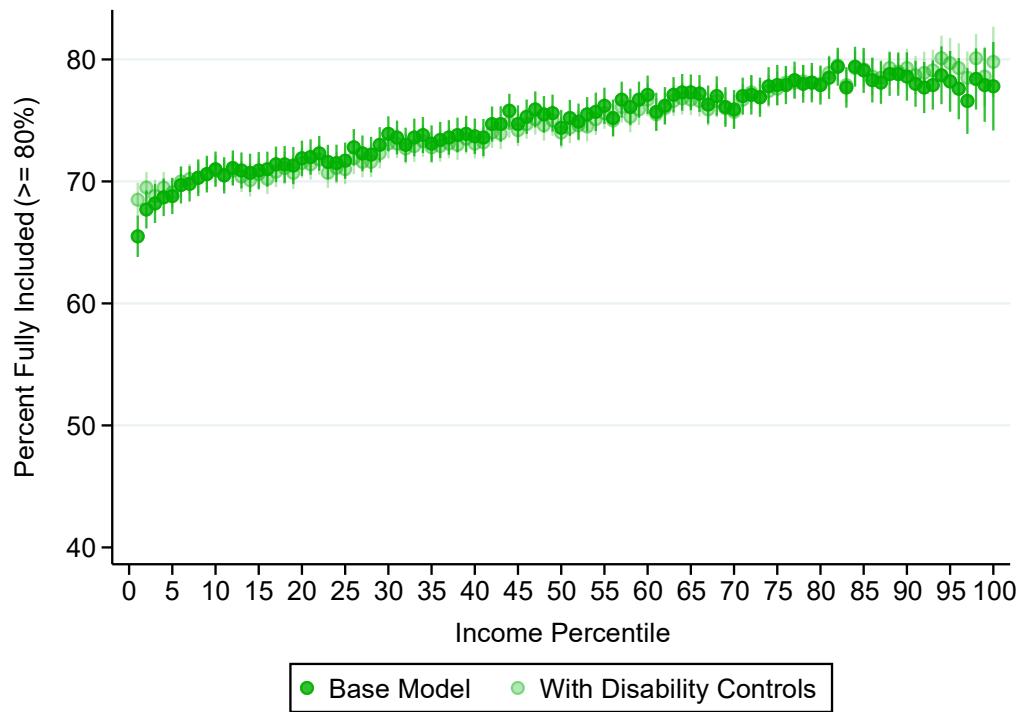
Notes. Pseudo-median income is calculated as the average income of observations within a narrow window of the true median income. DRB approval number: CBDRB-FY25-0309.

Fig. S3. Special education (A) and 504 plan (B) receipt by sex and income percentile
 Panel A. Special education



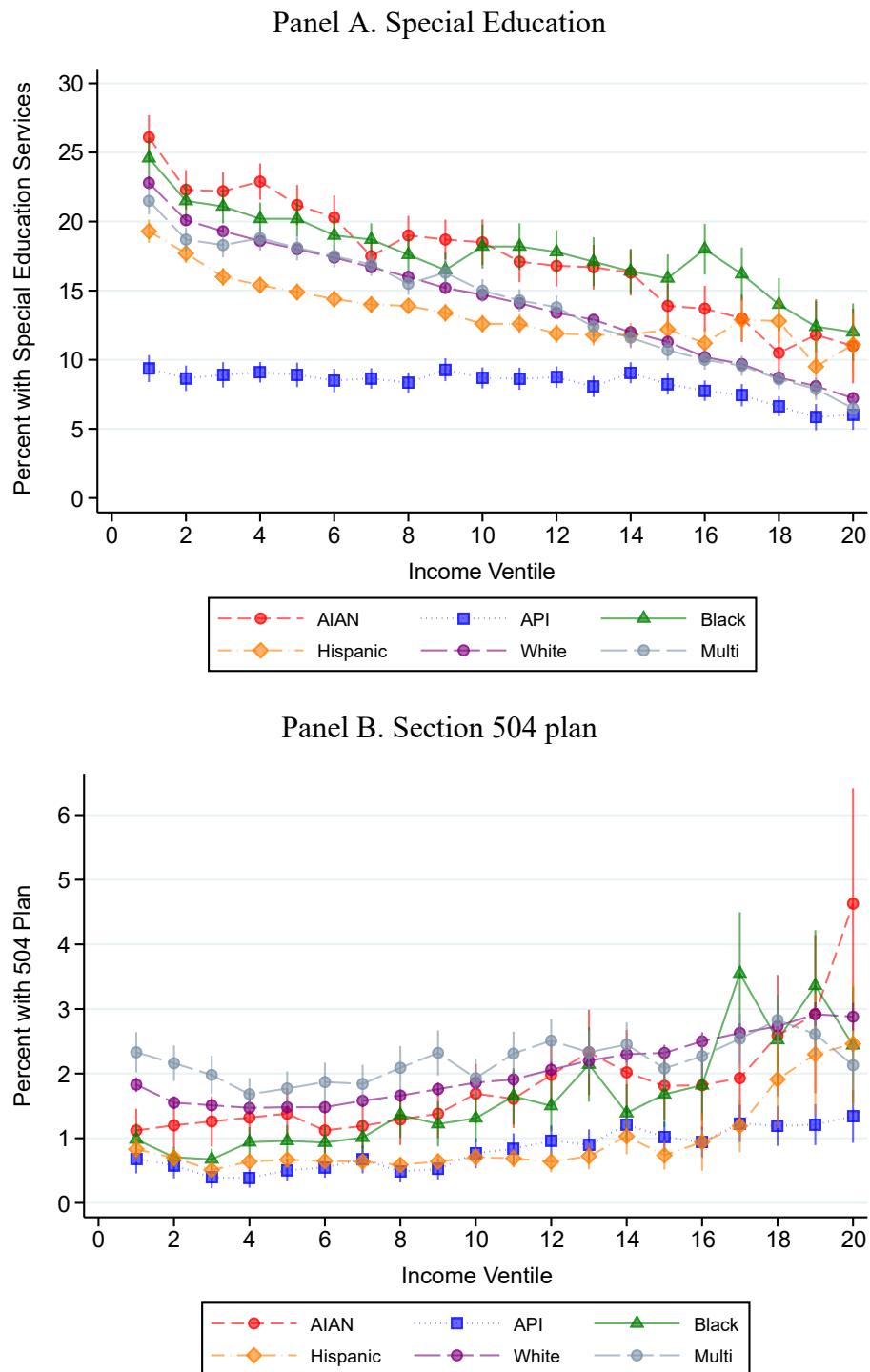
Notes. “Overall” identification rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, grade, and a linear trend in year. “Within school” estimates come from models incorporating school fixed effects. Models by sex are each run separately. DRB approval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

Fig. S4. Placement in an inclusive educational setting (80% or more of the day in a general education classroom) by income percentile



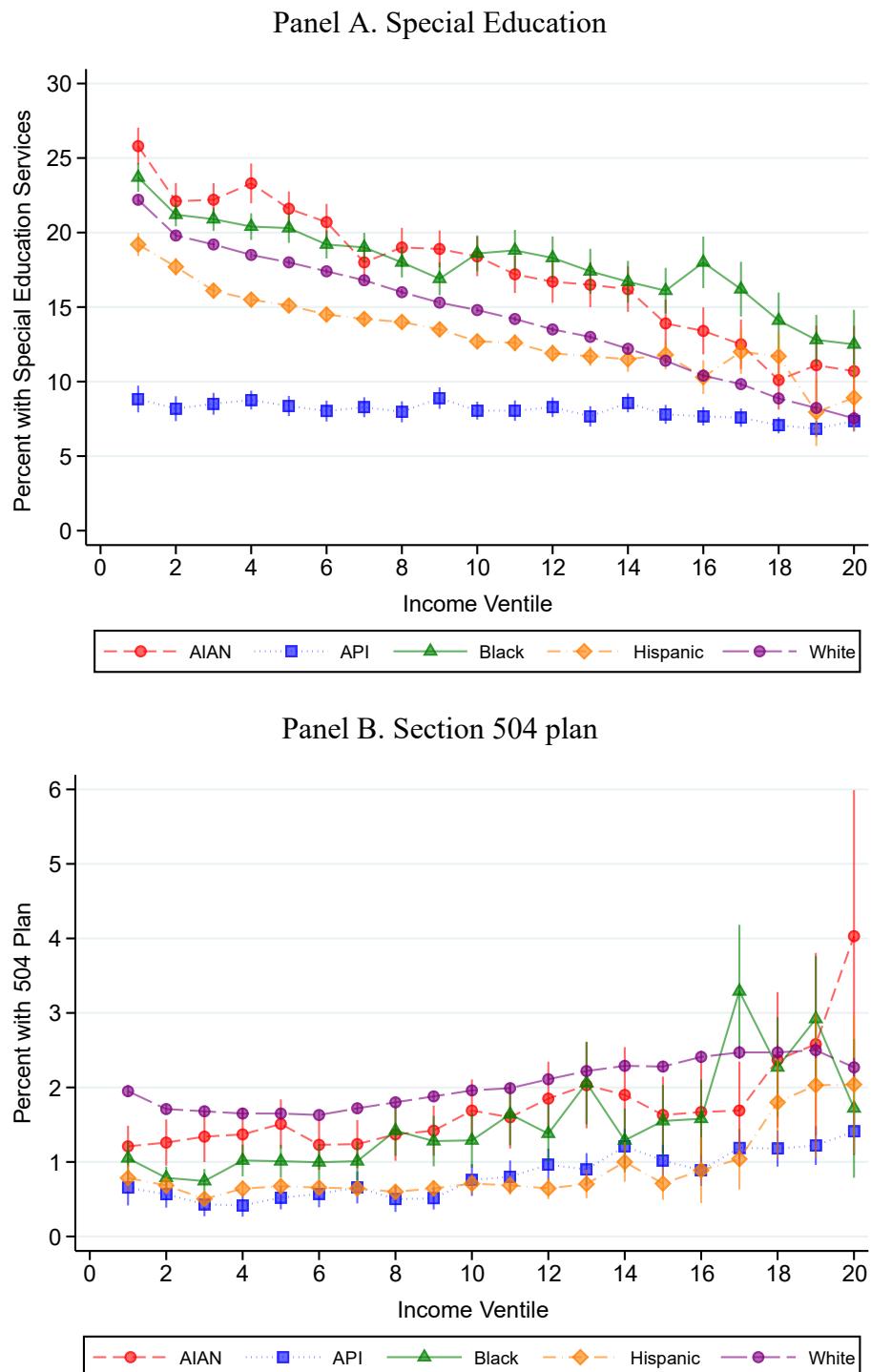
Notes. Full inclusion is defined as spending 80% or more of the day in a general education classroom and is recorded in each student's plan for special education services. Because only students receiving special education have a specified placement setting, models are run using only students receiving special education services. "Base model" inclusion rates are regression-adjusted means by income percentile estimated with models controlling for race/ethnicity, sex, grade, and a linear trend in year. "With disability controls" estimates come from models incorporating controls for a student's primary disability eligibility category. DRB approval number: CBDRB-FY25-0309

Fig. S5. Special education (A) and 504 plan (B) receipt by race/ethnicity and income ventile including Multiracial students



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

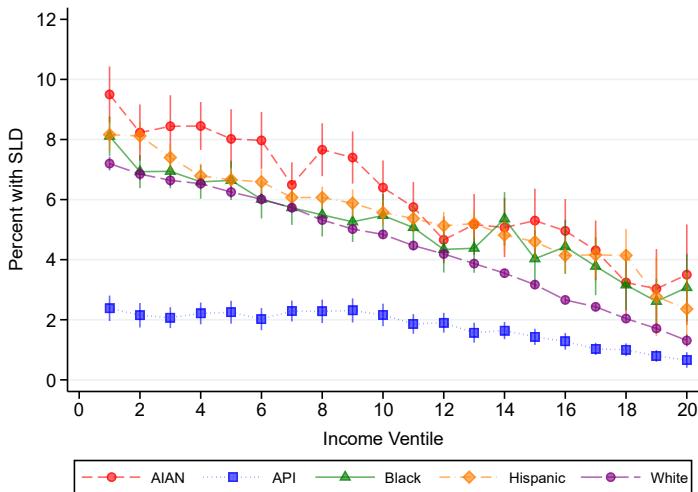
Fig. S6. Within school estimates of special education (A) and 504 plan (B) receipt by race/ethnicity and income ventile



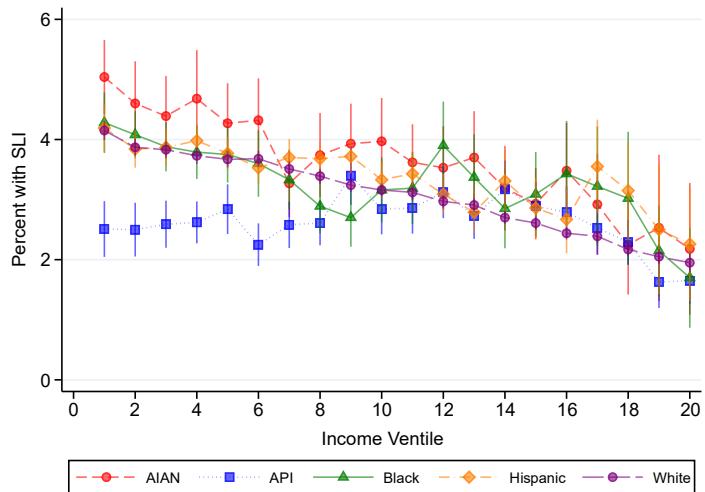
Notes. Identification rates are regression-adjusted means by income ventile estimated with models controlling for sex, grade, a linear trend in year, and school fixed effects. Models are run separately by race/ethnicity. Abbreviations are as follows: AIAN is American Indian/Alaska Native, API is Asian/Pacific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

Fig. S7. Special education identification by disability (A-D), race/ethnicity and income ventile

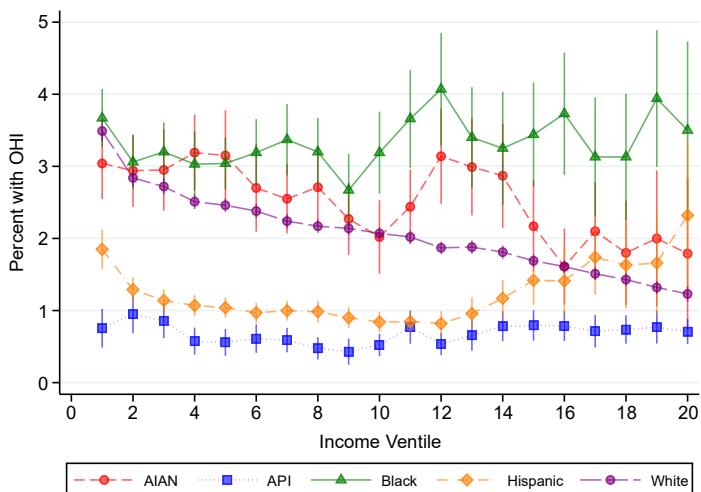
Panel A. Specific learning disability



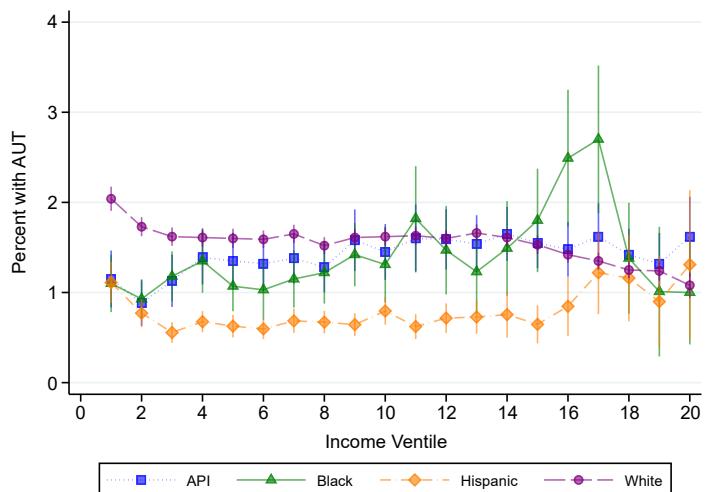
Panel B. Speech or language impairment



Panel C. Other health impairment



Panel D. Autism



Notes. Identification rates are regression-adjusted means by income ventile estimated with models controlling for sex, grade, and a linear trend in year. Models are run separately by race/ethnicity and by disability category. American Indian/Alaska Native students are omitted from the autism estimates due to small sample sizes. Abbreviations are as follows: SLD is specific learning disability; SLI is speech or language impairment; OHI is other health impairment; AUT is autism; AIAN is American Indian/Alaska Native, API is Asian/Pacific Islander. DRB approval number: CBDRB-FY25-0309.