From Rank to Label: How Early Academic Rank Shapes Educational Diagnoses and Mental Health Outcomes

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Abstract

This study uses rich Canadian census and administrative data to examine the causal effects of early academic ranking on educational diagnoses and long-term mental well-being. Leveraging within-classroom variation among students with similar abilities, I find that moving from the 0–5th to the 10–15th percentile reduces learning disability diagnoses by 34% and mental health conditions by 16%. Conversely, shifting from the 85–90th to the 95–100th percentile increases gifted diagnoses by 27%, showing that teacher perceptions and behaviors are influenced by relative performance. Similar rank variation also lower adult mental health challenges by 12% and boost learning-related self-esteem by 21%.

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1 Introduction

Imagine two students of identical ability: by sheer chance, one might rise to the top of their class while the other blends in among a group of high achievers. Despite their equal abilities, this seemingly minor difference in rank can influence both immediate outcomes—such as grades and graduation rates—and long-term economic prospects, including future income (Murphy et al., 2020; Kiessling et al., 2021; Denning et al., 2023).

This paper advances our understanding of the rank effect in two ways. First, it provides pioneering evidence that a student's academic rank influences their likelihood of receiving educational diagnoses—including learning disabilities, giftedness, and mental health conditions. The research exploits an institutional feature where parents receive only categorical performance feedback while educators observe continuous grades. This information asymmetry allows us to isolate teacher and institutional responses from parental influences, revealing how rank affects educator assessments. Crucially, these findings illuminate a previously unexplored source of educational inequality, as the government offers up to $50,000 annually for the most severe diagnoses—redirecting scarce resources based on what is, in part, random classroom placement. Second, the paper demonstrates that childhood academic rank affects long-term psychological well-being, as evidenced by mental health outcomes and learning confidence in adulthood.

To conduct this analysis, I use administrative data from British Columbia covering 2000–2021, focusing on each student's fourth-grade rank within their school cohort. These ranks are based on a standardized provincial assessment taken by over 800,000 students, which I link to the 2021 long-form Canadian Census for detailed mental health information.

I identify causal effects, following Murphy et al. (2020) and Denning et al. (2023), by leveraging the idiosyncratic variation in rank among students with comparable academic abilities in similar school cohorts. Specifically, I allow for abilities to differ across various school-cohort types and control for school-cohort fixed effects, as well as key demographic variables (gender, ethnicity, and parental income). I demonstrate that substantial rank variation persists even after accounting for individual skills and school cohort characteristics. Recognizing that the impact of rank may be non-linear, I employ a flexible specification that captures differential effects across the rank spectrum.

I find that classroom rank significantly impacts the likelihood of receiving educational diagnoses and has lasting impact on mental health and learning confidence. These effects are especially pronounced at the extreme ends of the rank distribution. For example, conditional on abilities, moving from the 0th–5th to the 10th–15th percentile reduces the likelihood of being diagnosed with a learning disability by 34% and with a mental health condition by 16%. It also lowers the probability of experiencing learning difficulties and mental health problems in adulthood by 21% and 12%, respectively. Conversely, moving from the 85th–90th to the 95th–100th percentile increases the probability of a gifted diagnosis by 27% and reduces long-term learning difficulties by 8%.

These patterns persist, albeit with smaller magnitudes, when comparing adjacent rank bands (e.g., 0–5% vs. 5–10%). Notably, similar or stronger effects are observed within the specific feedback categories provided to students and parents, indicating that teacher or institutional responses to rank are the primary drivers of these outcomes. Furthermore, rank in 7th grade affect diagnosis outcomes in a similar manner.

The impact of academic rank on diagnoses is substantial surpassing the diagnosis gaps observed across demographic groups, such as income or gender. Moreover, the heterogeneity analysis indicates that the impact of rank is relatively uniform across these demographic characteristics. Additionally, I investigate whether these outcomes vary based on the subject used to determine classroom rank—numeracy, reading, or writing—and discover that mathematical rank, in particular, significantly influences gifted identification, whereas rank in other subjects does not yield notable effects.

Next, I conduct a series of validation exercises to ensure the robustness of my findings. First, I run placebo tests using physical health diagnoses—such as blindness or deafness—that should not be related to classroom standing. As expected, these tests show no association between academic rank and those diagnoses. Second, I verify that passive sorting does not drive my results, assess the sensitivity of my findings to various functional form assumptions, and examine whether the estimated effects differ by school-cohort size.

My results are important for two main reasons. First, even small rank differences in primary school have lasting consequences: they alter self-reported mental health in adulthood and materially impact the likelihood of formal clinical diagnoses in childhood. Whereas Kiessling and Norris (2023) document high-school rank effects on depression scales using survey data from U.S. students, I extend this evidence using comprehensive administrative data covering the universe of students in British Columbia and demonstrate that rank shapes both subjective well-being and actual mental-health diagnoses. These findings cast doubt on early academic evaluations that may inadvertently foster short and long-term psychological harm.

Second, my analysis supports the two key mechanisms proposed by previous studies to explain how student rank influences future outcomes. The first hypothesis suggests that an individual's rank within their peer group serves as a critical indicator of their abilities, especially when information is imperfect. While earlier research has largely focused on short-term effects (e.g., Murphy & Weinhardt, 2020), this study demonstrates that the influence of rank on perceived learning ability can endure into adulthood, highlighting the long-lasting implications of early academic standing.

The second hypothesis addresses how external actors respond to students' ranks. Prior research offers limited support for this mechanism: Elsner and Isphording (2017, 2018) and Pagani et al. (2021) show that professors are largely unaffected by student rank, while Murphy and Weinhardt (2020) find minimal parental response. In contrast, my findings show that rank—even after controlling for inherent ability and the specific feedback given to parents and students—significantly influences whether a student is diagnosed with a learning disability or identified as gifted in the same academic year. This suggests that teachers' assessments depend not only on absolute performance but also on students' relative position among their peers.

While previous research has examined demographic biases—such as those related to race, gender, or socioeconomic status (Skiba et al., 2006; Harry & Klingner, 2006)—academic rank has not been considered as a source of diagnostic bias. By highlighting how relative standing can guide teachers' perceptions and assessments, this study uncovers a new mechanism through which educational practices may distribute support unequally. These findings highlight the need for increased awareness, universal testing based on grades, and targeted training for educators to mitigate rank-based biases, ensuring that all students receive fair and appropriate support aligned with their actual needs and abilities.

The remainder of the paper is organized as follows. Section 2 describes the institutional setting and details the administrative and census data that underpin the analysis. Section 3 outlines the empirical framework and identification strategy. Section 4 presents the main findings on the impact of academic ranking on educational diagnoses and long-term mental well-being. Finally, Section 5 concludes.

2 Institutional Setting and Data

This study leverages high-quality administrative data from Canada to examine the impact of academic rank on student diagnoses and long-term mental health outcomes. Specifically, I utilize the BC K–12 dataset, which tracks the entire student population in British Columbia from kindergarten through high school graduation. The analysis focuses on students born between 1988 and 2003 who attended schools within the province. For these cohorts, the dataset offers comprehensive information, including detailed demographic profiles, transcript grades, and annual special needs designations.

2.0.1 FSA

A key component of the BC K–12 dataset is the Foundation Skills Assessment (FSA), a province-wide standardized test administered to students in grades 4 and 7. Introduced in 2000 and revised in 2008 and 2017—with adjustments to its administration schedule—the FSA is typically conducted early in the school year.[2] The assessment measures student proficiency in reading, writing, and

[2] From 2000 to 2007, the FSA was administered in May; from 2008 to 2016, it took place in January; and since 2017, it has been conducted in October.

numeracy, aiming to provide an overview of students' foundational skills rather than serving as a high-stakes exam. Notably, FSA results do not appear on transcripts nor affect grade promotion or course placement.

Each student's FSA performance is recorded on a 100-point scale, accessible to educational institutions and teachers, while parents and students receive feedback in one of three descriptive categories: "emerging", "on track", or "exceeding". [3] With participation rates consistently exceeding 80% among eligible students, the FSA is a crucial tool for evaluating and comparing student achievement across the province. It remains the only standardized assessment in British Columbia before grade 10. For further details on participation rates, Appendix Table 5 presents annual FSA completion data for grade 4 students.

2.0.2 Special Needs

The BC K–12 dataset includes annual records that document students' special needs, which are grouped into 13 distinct categories. These classifications are defined by the *Special Education Services: A Manual of Policies, Procedures and Guidelines*[4]. According to the manual, "special needs" refers to a spectrum of challenges—physical, intellectual, sensory, emotional, behavioral, and learning difficulties—as well as exceptional talents. The identification process typically begins with observations made by teachers or parents and is often followed by a formal diagnosis from a qualified professional, such as a physician or psychologist. For a student to be diagnosed, their difficulties must be persistent and significantly disruptive to their learning or the overall classroom environment. Once classified, students receive an Individual Education Plan (IEP) and may access a range of in-school support services, including learning assistance, speech-language therapy, and counseling or psychological services.

This study focuses on three specific diagnostic categories: Learning Disability, Gifted, and Mental Health. Below is an breakdown of the diagnostic process for each category.

[3] In any given year, approximately 20% of students fall into the "emerging" or "exceeding" performance categories, while 60% are categorized as "on track."

[4] British Columbia Ministry of Education, 2016

- Learning Disability: This category includes students identified with learning disabilities, mild intellectual disabilities, or severe learning disabilities. Diagnosis generally requires formal testing, often initiated by teachers when persistent learning challenges are observed. For instance, to be diagnosed with mild intellectual disabilities, students must score two standard deviations below the average on standardized assessments.

- Gifted: Identification of gifted students is based on broader criteria, encompassing teacher observations, anecdotal records, nominations by educators, and formal assessments. Giftedness is less rigidly defined, requiring multiple indicators to substantiate a student's exceptional intellectual or creative abilities.

- Mental Health: For mental health needs, I adopt the approach used by Jones et al. (2024), which combines two categories, using the same data: moderate behavioral needs or mental illness, and intensive behavioral needs and serious mental health issues. Teachers play a critical role in recognizing behavioral and socio-emotional challenges that disrupt learning or social interactions, often prompting referrals for further assessment.

2.0.3 Mental Health and Perceived Ability to Learn

Data on mental health and learning difficulties into adulthood are sourced from the 2021 Canadian Census long-form survey, which was administered to a representative 25% sample of the population aged 15 and older. This survey collected information on various daily activity challenges faced by respondents. I focus on two specific survey questions that assess mental health and learning difficulties:

- 18.d: "Does this person have any difficulty learning, remembering, or concentrating?"

- 18.e: "Does this person have any emotional, psychological, or mental health conditions (e.g., anxiety, depression, bipolar disorder, substance abuse, anorexia, etc.)?"

Respondents answered using a four-point scale: No, Sometimes, Often, or Always. While these measures are self-reported, the ability to control for confounding factors and the categorical nature of responses enables the analysis of how early academic rank influences both the presence and severity of long-term mental health and learning challenges.

2.0.4 Demographics

To explore the heterogeneity of the impact of rank and control for outcome variations across demographic groups, the analysis will incorporate key background characteristics, including age, gender, minority status (proxied by language spoken at home), and Indigenous status—all of which are available in the BC K-12 dataset. Furthermore, family income will be assessed by linking the BC K-12 data with the parents' T1 Family File (T1FF), derived from tax records.

2.0.5 Later outcomes

To analyze later outcomes, I utilized the linkage between the British Columbia (BC) K-12 education data and two key datasets: the Postsecondary Student Information System (PSIS) and the Canadian Apprenticeship Registrations and Certifications (RAIS). The PSIS provides detailed information on all students attending post-secondary institutions in Canada, including the programs they enrolled in, the duration of their studies, and their completion status. This linkage enables us to examine the impact of early educational rank on various post-secondary academic outcomes, such as bachelor's degree enrollment, fields of study, program specifics, and the educational institutions from which students graduated. Additionally, the BC K-12 dataset is connected to the T1 Family File (T1FF), which records individuals' earnings as soon as they file their taxes. This linkage allows for an analysis of how early academic performance influences earnings in adulthood, even up to 17 years later.

2.1 Descriptive Statistics:

The sample includes all British Columbia students who took the FSA in fourth grade, starting from the test's inception in 2000. I restrict the sample to first-time FSA takers of typical school age, in cohorts of 10-90 students (equivalent to 1-3 classrooms). This yields approximately 40,000 students per academic year, totaling 826,100 students. Of these, 187,300 completed the 2021 Census long-form survey—reflecting its balanced 25% distribution and age requirements (15+ years).[5] Sample sizes for later-life outcomes are smaller as recent cohorts have not yet reached the relevant age thresholds.

Table 1: General Descriptive Statistics

Students Descriptive Variables:	**Population**	**Mean (%)**
Female	826,160	50.0
Male	826,160	50.0
Minority	826,160	24.0
First Nations	826,160	12.0
Non English Speaker	826,160	16.0
Diagnosis outcomes:		
Mental Health Diagnosis (4th)	826,160	1.4
Learning Disability Diagnosis (4th)	826,160	1.5
Gifted Diagnosis (4th)	826,160	1.1
Census outcomes:		
Mental Health (Age 24–26)	187,830	22.6
Difficulty Learning (Age 24–26)	187,830	12.1
Educational & labor market outcomes:		
Average Score (7th Grade)	606,600	60.0
High School Completion	514,700	82.0
Bachelor Enrolment	478,400	43.0
STEM Enrolment	478,400	15.0
Income (Age 24)	259,000	$25,400
Income (Age 26)	176,600	$31,200

Note. Values are rounded per Statistics Canada's guidelines. Sample sizes vary due to age restrictions in the Census (administered to 25% of those aged 15+) and labor market data (restricted to students old enough for post-secondary outcomes).

Table 1 presents the descriptive statistics of the sample. The distribution between male and female students is nearly balanced. Minority students, defined as those who do not speak French or English at home, the two official languages of Canada, comprise 24% of the sample. The term 'First Nations' refers to students who identifies itself as a descendants of the First Nations people, a status that is directly recorded within the BC-K-12 dataset. 'Non-English Speaker' denotes the

[5]The sample is balanced across respondents and non-respondents to the Census.

proportion of students who are not fluent in English by Grade 4. Approximately 4% of students were diagnosed with one of the specified conditions in 4th grade. Among those who responded to the Census, 22% reported experiencing mental health challenges at least occasionally, while 12% indicated difficulties learning.

3 Empirical Framework

3.1 Rank definition

In this study, the primary variable of interest is each student's relative position within their cohort, as determined by their performance on the grade 4 FSA exam. I use this ranking as a proxy for academic standing throughout the year. To facilitate meaningful comparisons across cohorts of varying sizes, I construct a standardized ranking measure that is invariant to differences in cohort size. Specifically, a student's rank is defined as their percentile position within their school-subject-cohort (SSC) based on FSA exam scores. By construction, this measure ranges from 0 to 1 and follows a uniform distribution.

Let N_{jsc} denote the size of the cohort in school s, cohort c, for subject j. For each individual i, their ordinal rank position within this group is denoted by n_{ijsc}, which increases with test score. The standardized rank R_{ijsc} used in the analysis represents the student's percentile rank in their class and is calculated as:

$$Rank = \frac{(\eta_{ijsc} - 1)}{(N_{ijsc} - 1)}, \quad R \in [0, 1] \tag{1}$$

Due to data limitations, rankings are computed at the school cohort level rather than at the individual classroom level. To validate this approach, I perform robustness checks on cohorts with fewer than 30 students—the provincial class size limit—as these groups are most likely to represent single classrooms.

3.2 Main Specification

I follow the empirical strategy of *Denning et al* (2023) and exploit, conditional upon ability, idiosyncratic variation in rank within similar classrooms which leads to the following estimating equation:

$$Y_{isc} = f(R_{ijsc})) + g_d(T_{ijsc}) + \delta_{jsc} + X_i\beta + \epsilon_{ijsc} \tag{2}$$

In this study, multiple outcome variables Y_{isc} will be analyzed, including the likelihood of diagnosis, mental health, and learning confidence. The primary variable of interest, R_{ijsc}, denotes the student's rank within their SSC on the 4th-grade FSA exam. To evaluate its effect in a non-parametric framework and thus allowing for non-linearity, ranks are divided into ventiles. Human capital is measured using the 4th-grade FSA score, modeled as a function $g(T_{ijsc})$, where T_{ijsc} is the test score for topic *j* of individual *i* in school cohort *sc*. Additionally, δ_{jsc} denotes a school cohort–topic fixed effect, capturing all unobserved factors specific to each school cohort and subject (quality of teachers, peers), while *X* includes student-specific characteristics, namely parental income (quintile), gender, ethnicity and an indigenous indicator.

To flexibly control for ability, I estimate $g(T_{ijsc})$ non-parametrically by partitioning ability into ventiles. This approach permits the effect of ability to vary across the distribution, accommodating potential non-linearities. One potential concern is that peer effects may vary according to a student's ability level, as demonstrated by *Booji et al. (2017)*. For instance, effective teaching might have a larger impact on high-ability students. If such heterogeneous effects are present, they could lead to omitted variable bias by influencing both a student's rank and their educational outcomes.

To address this issue, following Denning et al. (2023), I allow abilities to map differently into outcomes based on the classroom's test score distributions, represented by the function $g_d(T_{ijsc})$. Specifically, I classify classrooms into five groups based on the mean and variance of test scores, yielding 25 distinct classroom types. This approach accounts for how the relationship between ability and outcomes differs across educational environments and leverages variation in the higher moments of the ability distribution to identify the rank effect. Section 3.5 addresses concerns regarding insufficient rank variation when comparing similar classrooms .[6]

The identifying assumption is that $\epsilon_{ijsc} \perp R_{ijsc}$ meaning the error term is uncorrelated with rank. This assumption could be violated if there is specification error in the model. However, I do not need to assume the complete absence of specification error; rather, I only require that any such error is unrelated to rank. To minimize potential specification error, the model allows ability to flexibly map into outcomes. Additionally, I provide robustness checks by testing alternative functional forms, such as using polynomials of abilities, to ensure the results are not sensitive to the choice of specification. In the next subsections I augment the simple specification and address different concerns about the empirical strategy.

3.3 Heterogeneous Effects Across Subjects

Prior research on educational rank frequently assumes that a student's relative standing is equally impactful across all subjects—for example, a high rank in mathematics is assumed to influence outcomes in the same way as an equivalent rank in English. However rank in specific subjects may have a differential impact on diagnostic outcomes—a nuance with important policy implications. To test for these differential effects, I extend the basic specification to aggregate subject-specific influences:

$$Y_{isc} = \sum_{j=1}^{J} f(R_{ijsc})) + \sum_{j=1}^{J} g_d(T_{ijsc}) + \delta_{sc} + X_i\beta + \epsilon_{isc} \tag{3}$$

In this equation, I sum over all topics j to account for the impact of rank in multiple topics on the Y_{isc}. By doing so, I can assess whether the rank effect is consistent across different subjects.

[6]Ideally, comparisons would be made among classrooms with nearly identical test score distributions, thus limiting the correlation between rank and heterogeneous classroom effects. However, if classrooms were identical there would be no rank variation to identify its effect. Nonetheless, our approach remains justified, as no study to date has established a robust link between these higher moments and educational outcomes (see Denning et al. (2023) for an extended discussion).

3.4 Diagnosis and Teacher referrals

The analysis focuses on fourth- and seventh-grade diagnoses to align with the FSA schedule, since the FSA is administered near the start of the academic year. These early-year rankings likely influence teachers' initial perceptions of student abilities, which in turn might influence whether a student is referred for diagnostic evaluation. One concern is that the FSA timing changed overtime. This shifting schedule raises a potential concern that a student's test rank could be influenced by an ongoing or recently completed diagnosis, rather than the diagnosis following from the student's performance or rank. Although students with a formal diagnosis—and thus an Individual Education Plan (IEP)—are exempt from taking the FSA, situations may still arise where a child's evaluation is in progress during the exam period, potentially influencing both their performance and subsequent ranking.

To address these timing concerns, I conduct several robustness checks. First, I reestimate the results using only data from the 2017 cohorts onward, when the FSA was consistently administered in October. Second, I examine diagnoses that occur in fifth and eighth grades, effectively shifting the diagnostic window beyond the FSA period. In both analyses, the results are similar to those obtained under the main sample.

To interpret the results as evidence of external responses, I assume that students with similar FSA exam abilities, demographic characteristics, and school cohorts have comparable diagnostic needs and would perform similarly on subsequent cognitive assessments (e.g., C tests).[7] Under this assumption, any systematic differences in diagnosis rates among otherwise comparable students can be attributed to external responses to rank—such as biases in teacher referrals, institutional practices, or proactive parental interventions.

To disentangle teacher bias from parental responses, I exploit a key institutional feature: the FSA results communicated to parents are categorized into discrete performance levels. Since rank varies continuously within these feedback categories while parents receive identical performance information, any rank effects observed within categories can be credibly attributed to teacher or

[7]Note: I do not have access to C tests, which are used to diagnose certain conditions.

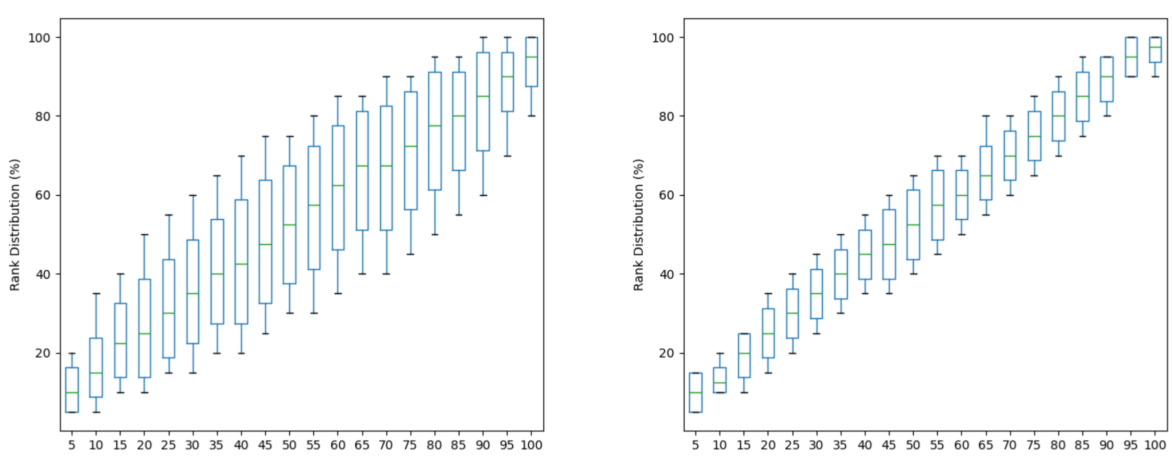
institutional factors rather than parental responses.

Current diagnostic practices and guidelines acknowledge limitations in identifying all clinical conditions, creating room for discretion in referral decisions. Educators might pay particular attention to students at the extremes of classroom achievement—both high and low performers—leading to increased recommendations for diagnostic testing among these students. To validate this interpretation, I conduct placebo tests analyzing the relationship between academic rank and diagnoses of purely physical conditions (such as visual or auditory impairments) where academic performance should have no causal effect.

3.5 Observed Variation in rank

As detailed in Section 3.2, the empirical strategy compares students across classrooms with similar means and variances in ability levels. Although this approach reduces rank variation, identification is achieved by exploiting differences in the higher moments of the classroom ability distributions. Figure 1 illustrates how rank variation changes as increasingly stringent classroom comparisons are applied.

Figure 1: Variation in Fourth-Grade Numeracy Ranks



A. Across all Cohorts B. Across similar Cohorts

These figures show how fourth-grade numeracy ranks vary across ability levels. Each box plot indicates the 10th, 25th, 50th (median), 75th, and 90th percentiles. Figure 1(a) includes all school cohorts, while Figure 1(b) focuses on classrooms with similar average ability and variance, then averages the resulting distributions.

Specifically, Figure 1.a presents the variation in rank conditional on ventile of ability when comparing students across all classrooms, while Figure 1.b shows the variation in rank within similar categories of classrooms. When looking at all classrooms, there is substantial variation in rank across the entire ability distribution. For instance, in the middle of the ability distribution, the 10th to 90th percentile distance in rank conditional on ability is over 40%, implying that students with an average ability level can occupy a wide range of ranks. At the extremes of the ability distribution, the variation is smaller, with a 10th to 90th percentile range close to 30%.

When examining similar classrooms (figure 1b), a comparable pattern emerges, though with reduced rank variation. In the middle of the ability distribution, the range between the 10th and 90th percentiles decreases to approximately 30%, while at the extremes, it narrows een further to 20%.[8]

Based on the analysis of these figures, I propose different range for rank variation that I will focus on, depending on the student's position within the ability distribution:

- For students at either end of the ability spectrum, I adopt a 10-percentile range threshold. This narrower band reflects the naturally constrained variation in these regions, where I observe rank fluctuations of about 15% between the 10th and 90th percentiles in both the highest and lowest ability ventiles.

- For students in the middle of the ability distribution, I employ a 20-percentile range threshold. This broader band accommodates the greater natural variation observed in this region, where the interquartile range (25th to 75th percentile) consistently spans at least 20%.

In summary, my analysis focuses on rank variations within a 20-percentile range for the middle of the ability distribution and a 10-percentile range at the extremes. Although this conservative approach is somewhat restrictive, it serves two key methodological purposes: it enhances the robustness of the results by concentrating on the most reliable variations in the data and establishes a credible lower bound for estimating rank effects.

[8]Detailed descriptive statistics on the average rank variation across these classroom specifications are provided in the appendix.

3.6 Sorting

In Canada, students are often assigned to schools based on their zip code, leading to a non-random distribution of students across schools. This process can result in certain groups, such as students from lower socio-economic backgrounds, being more frequently placed in classrooms with lower average abilities. Such sorting could spuriously correlate student characteristics, such as socio-economic status, with their academic rank and subsequent outcomes, potentially biasing the rank estimates.

By comparing students from similar classrooms, I minimize the potential bias resulting from the sorting of certain children into specific classrooms as was shown in *Denning et al 2023*. To validate this, balance tests are presented in Table 2. I do not observe the same result that comparing students from similar classrooms removes passive sorting. However, even if these tests show that demographics is significantly correlated with rank, the magnitude of these correlations are extremely small. In the regression analysis, I control for these characteristics. As a result, I proceed under the assumption that any residual bias stemming from passive sorting on unobserved characteristics is likely to have only a minimal impact on the estimates.

Table 2: Balancing tests (demographics on rank)

Category	All classrooms	Similar classrooms
Gender	-0.006***	-0.006***
	(0.0001)	(0.0003)
Minority	-0.003***	0.001***
	(0.0001)	(0.0002)
Indigineous	0.006***	-0.002***
	(0.0001)	(0.0002)
Non English 4	0.001***	-0.002***
	(0.0001)	(0.0002)

In this table, I regress rank on demographic variables while controlling for school-subject-class (SSC) fixed effects. Across all classrooms, I incorporate ability by ventile. For classrooms that are similar, I introduce an interaction term between ventile of ability and the statistical moments of the classroom distribution.

3.7 Measurement error

To isolate the impact of rank from other influencing factors, many studies, including this one, rely on standardized tests administered to all students. These tests provide significant variation in score distributions across schools, subjects, and cohorts, offering a useful basis for the analysis (Murphy et al., 2020; Denning et al., 2023). However, using test scores as proxies for innate ability and rank poses challenges, as test performance may be influenced by non-random factors such as test-day conditions or disparities in school resources. To address this concern, researchers such as Denning et al. (2023) and Goulas et al. (2023) have conducted simulations to quantify the potential biases introduced by measurement error. Their findings suggest that any such biases are relatively minor and would, if anything, attenuate the estimated rank effect. Consequently, the observed impact of rank in our analysis is likely a conservative estimate, implying that the true effect may be even larger if measurement error is present.

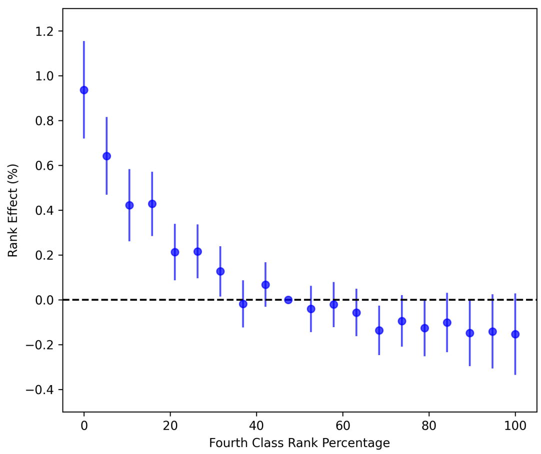
4 Results

In this section, I present the main findings of the study, derived from estimating Equation 2 across a range of outcomes. The results are displayed both graphically, showcasing the regression coefficients, and in tables, where they are expressed as relative percentages. These percentages are calculated by dividing the coefficients by their base frequencies, providing a clearer representation of the proportional impact relative to the initial likelihood of the outcomes. Additionally, the analysis emphasizes the relevant variations discussed in Section 3.5.

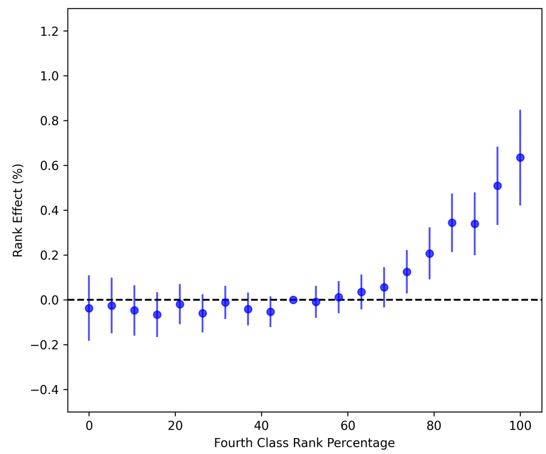
4.1 Impact of Academic Rank on Educational Diagnoses

This section explores how students' rankings in 4th grade influence their likelihood of being diagnosed with special conditions. Figure 2 shows the impact of academic ranking on the likelihood of being diagnosed with cognitive diagnostic in 4th grade among children of similar abilities in similar classrooms.

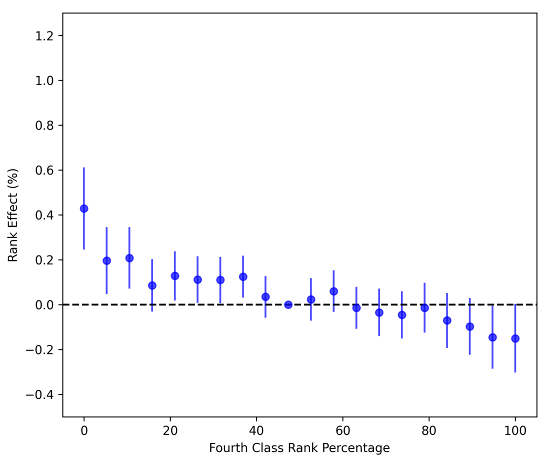
Figure 2: Effect of Fourth-Grade Academic Rank on Diagnostic Outcomes in Fourth Grade



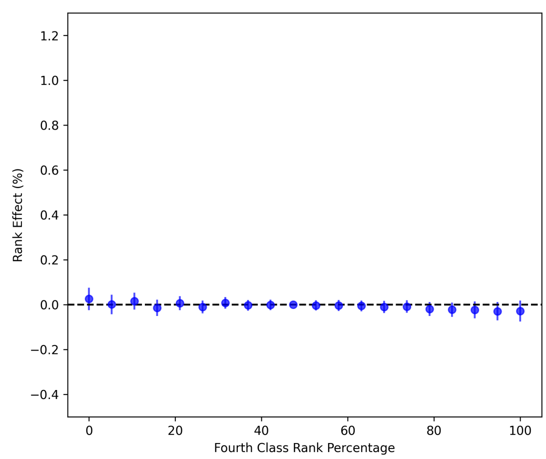
(a) Learning Disability Diagnosis



(b) Gifted Diagnosis



(c) Mental Health Diagnosis



(d) Deaf Diagnosis

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in fourth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

Panel A illustrates the effect of rank on learning disability diagnosis, revealing pronounced non-linearity: occupying a higher rank does not significantly reduce the likelihood of being diagnosed, whereas being at the lower end of the rank distribution substantially increases that likelihood. For example, moving from the bottom 5 percent of the class to the 10th–15th percentile decreases the probability of diagnosis by 0.57 percentage points. Given that only 1.5% of students receive a learning disability diagnosis in 4th grade, this translates into a sizable 38% relative increase for the lowest-ranked students.

Panel B examines the impact of rank on gifted diagnoses and again shows a marked nonlinearity. In this case, being low-ranked does not notably decrease the likelihood of being classified as gifted, but high academic rank markedly increases it. Specifically, moving from the 85th–90th percentile to the 95th–100th percentile raises the probability of a gifted diagnosis by 0.3 percentage point—equivalent to a 27% relative increase.

A similar pattern emerges with mental health diagnoses: being near the bottom of the class rank distribution significantly increases the likelihood of receiving a diagnosis. For example, moving from the lowest 5 percent of the class to the 10th–15th percentile reduces the probability of a mental health diagnosis by 0.22 percentage points—an 16% relative decrease.

To put the magnitude of these effects into perspective, they are larger than the differences observed across demographic groups. Using estimates from the same regression, children from the lowest quintile of the income distribution are diagnosed as gifted only 0.3 percentage points less often than children from the highest quintile, and there is no significant difference across income groups for learning disabilities. Similar patterns are observed across other demographic variables.

Placebo Tests: To validate the findings, I conducted placebo tests by analyzing the effect of academic rank on diagnoses unrelated to rank, such as blindness and deafness, which are determined through medical assessments and should be independent of performance or teacher perceptions. As expected, Panel D in Figure 2 shows no significant impact of rank on the likelihood of being deaf. Additional figure 7 in the annex showcase that there is no significant effect on blindness diagnoses. The placebo tests reinforce the main findings by demonstrating that rank effects are specific to diagnoses where teacher perception and referral play a crucial role. It suggests that teachers' responses to student rank significantly influence the likelihood of being diagnosed with learning difficulties, giftedness, and mental health issues, rather than these effects being driven by unobserved variables correlated with rank.

7th Grade Diagnosis: The patterns observed for 4th-grade diagnoses persist when examining diagnostic outcomes in 7th grade—the final year of primary school in British Columbia (see Figure 8 in the Appendix). Table 3 presents estimates of rank effects on diagnoses across both grades, revealing striking consistency in both magnitude and relative impact. For example, moving from the 85th-90th percentile to the 95th-100th percentile increases the probability of a gifted diagnosis by 27% in 4th grade and 33% in 7th grade. Differences in relative effects between grades largely reflect variations in the baseline prevalence of diagnoses within each year, rather than changes in the underlying point estimates. This is evident in the case of learning disability diagnoses, where the percentage point effect is slightly larger in 7th grade (0.64 vs. 0.52 percentage points), but the relative impact is greater in 4th grade due to lower baseline prevalence. This consistency in rank effects across grade levels provides strong support for the robustness of the main findings.

Table 3: Impact of Fourth-Grade Academic Rank Shifts on Diagnostic Outcomes

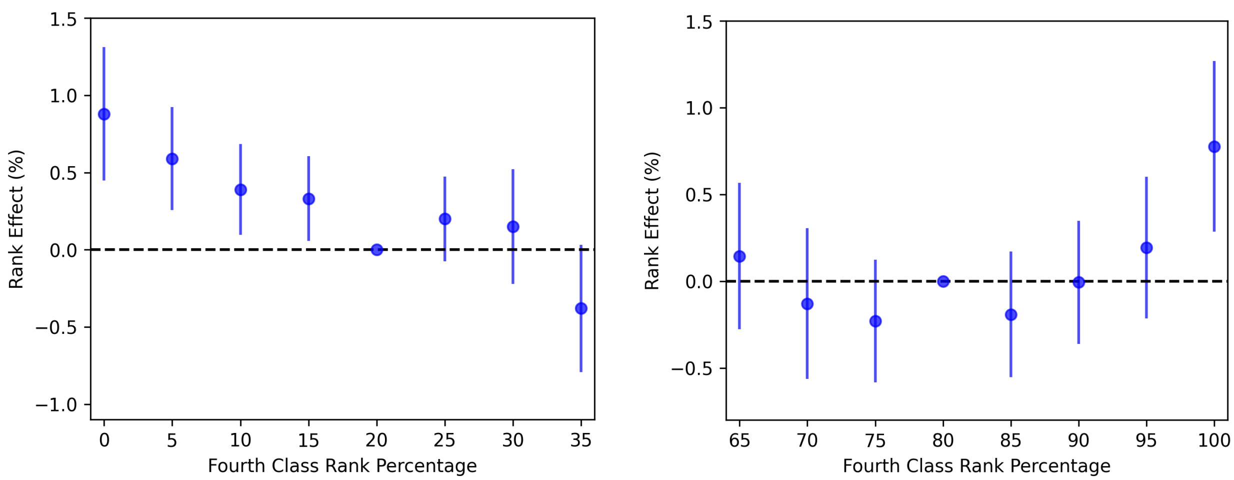
Diagnosis	**0–5% → 10–15%**	**25–30% → 45–50%**	**50–55% → 70–75%**	**85–90% → 95–100%**
Learning Disability (4th Grade)	-34.33***	-14.20***	-5.69	-0.33
Learning Disability (7th Grade)	-17.88***	-6.45***	-4.09**	-0.89
Mental Health (4th Grade)	-15.71***	-9.29**	-2.69	-3.84
Mental Health (7th Grade)	-24.83***	-9.01***	-3.18	1.35
Gifted (4th Grade)	-0.93	1.82	19.66***	26.91***
Gifted (7th Grade)	-2.25	0.85	9.66***	33.35***

Notes: Each column shows the estimated percentage point change in the probability of being diagnosed within the same academic year when a student's rank moves from the lower to the upper percentile range shown in the column header. These estimates are computed as differences in the coefficients from Equation 6, with statistical significance assessed via F-tests. For example, the first column reflects the change in probability when a student's rank moves from the 0–5% to the 10–15% band. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Diagnosis in 5th and 8th Grade: To address potential concerns about FSA timing, which varied between early-year, mid-year, and end-of-year administration across cohorts, I examine diagnoses in fifth and eighth grades. This approach shifts the diagnostic window beyond the FSA testing period (results presented in Figures 9 and 10 in the appendix). The patterns remain remarkably consistent with the main findings. For example, moving from the bottom 5 percent to the 10th-15th percentile of class rank reduces the probability of a learning disability diagnosis by 0.57 percentage points in fourth grade compared to 0.63 percentage points in fifth grade. As an additional validation exercise, I restrict the analysis to the 2017 cohort, where FSA tests were administered in October. These results (Figures 11 and 12) again demonstrate similar patterns.[9]

Teacher Responses to rank: To isolate teacher and institutional responses to student rank—separating them from potential parental reactions—I leverage variation in rank within each performance feedback category ("Emerging," "On Track," or "Exceeding"). This design allows me to examine how rank affects outcomes while holding constant the categorical information available to parents and students. While complete common support is unobtainable (as no cohort consists entirely of "Emerging" or "Exceeding" students), I restrict the analysis to the overlapping range of ranks within each category. Figures 3(a) and 3(b) present these estimates: panel (a) shows the effect of rank on learning disability diagnoses for "Emerging" students, while panel (b) displays the corresponding results for gifted designations among "Exceeding" students.

Figure 3: Effect of Fourth-Grade Academic Rank on Diagnostic Outcomes in Fourth Grade conditional on Parental Feedback



(a) Learning Disability Diagnosis (b) Gifted Diagnosis

These figures show the estimated impact of fourth-grade academic rank (measured in ventiles) on the probability of receiving educational diagnoses in fourth grade (expressed in percentage points). Estimates are derived from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. Figure 3(a) presents results exclusively for students categorized as "Emerging," while Figure 3(b) shows results for "Exceeding" students. The model controls for minority status, gender, and parental income, and includes student ability indicators (in ventiles) interacted with school-subject-cohort (SSC) test score distributions. SSC groups are divided into 25 categories based on mean and variance of test scores.

Even within these performance categories, rank effects remain statistically significant, with point estimates that are comparable to—or larger than—those in the full sample. As expected, standard errors increase due to smaller subsample sizes. For instance, among students in the

[9] Analysis of new diagnoses yields consistent results (Figures 13 and 14).

"Emerging" category, moving from the 5th percentile to the 10th–15th percentile reduces the probability of a learning disability diagnosis by 0.48 percentage points—slightly smaller than the 0.57 percentage point reduction in the full sample. Conversely, in the "Exceeding" group, advancing from the 85th–90th percentile to the top 5th percentile increases the probability of a gifted diagnosis by 0.77 percentage points, more than double the 0.3 percentage point effect observed in the full sample.[10]

These findings strongly indicate that teacher perceptions, shaped by students' relative class performance, drive diagnoses for learning disabilities, mental health conditions, and giftedness, while purely medical diagnoses remain independent of rank. Over-reliance on relative performance may lead to misdiagnoses that carry long-term consequences, denying genuinely at-risk students the support they need. Consequently, there is a clear need for policies that emphasize absolute performance over rank to ensure equitable and effective resource allocation.

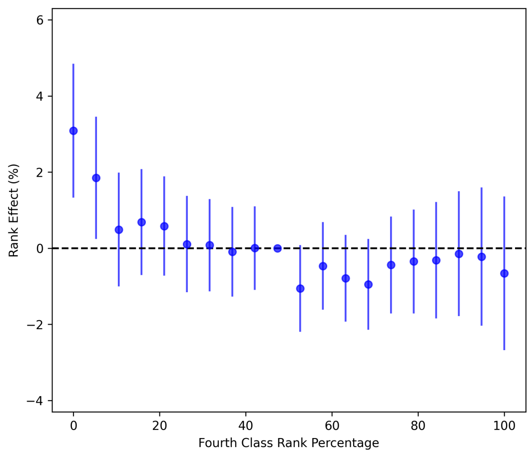
4.2 Impact of Rank on Mental Health and Perceived Learning Ability

In this section, I analyze the long-term effects of 4th-grade class rank on students' self-reported mental health and learning abilities later in life, as captured in the 2021 Canadian Census. Figure 3 highlights the relationship between 4th-grade rank and self-reported difficulties later in life.

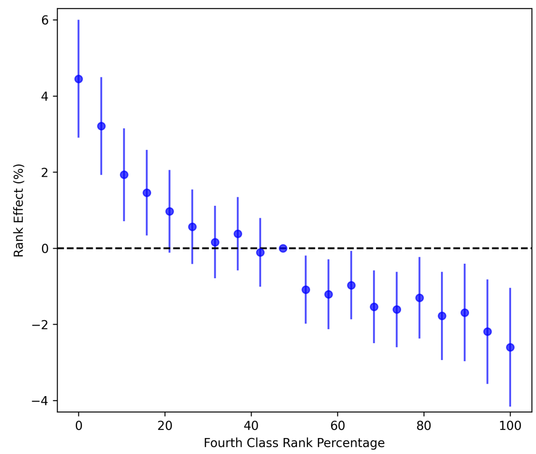
Panel A and B demonstrate that a student's rank in fourth grade exerts a significant and enduring influence on self-perceived mental health and cognitive abilities. In particular, Figures 4 and 5 show that students in lower class-rank percentiles are more likely to report mental health and learning difficulties in adulthood. Moving from the 0–5th percentile to the 10–15th percentile of class rank lowers the likelihood of reporting learning difficulties by about 3 percentage points, while the probability of experiencing mental health challenges similarly declines by roughly 3 percentage points over the same rank improvement. These estimates underscore how fourth-grade class rank continues to shape not only academic outcomes but also perceived cognitive capacity and mental well-being later in life. Notably, these changes represent substantial relative differences—an

[10] Results for the "On Track" category appear in Appendix Figure 16.

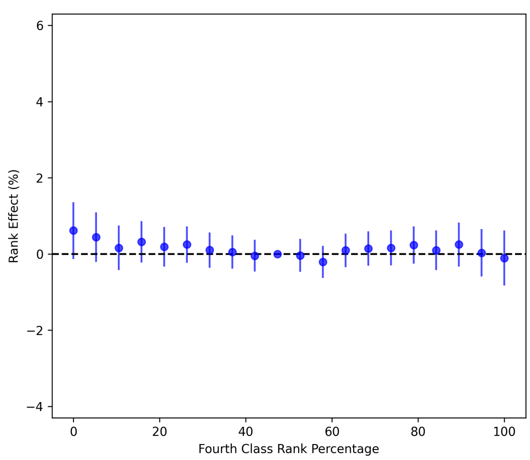
Figure 4: Impact of Fourth-Year Academic Rank on Mental Health and Learning Difficulties



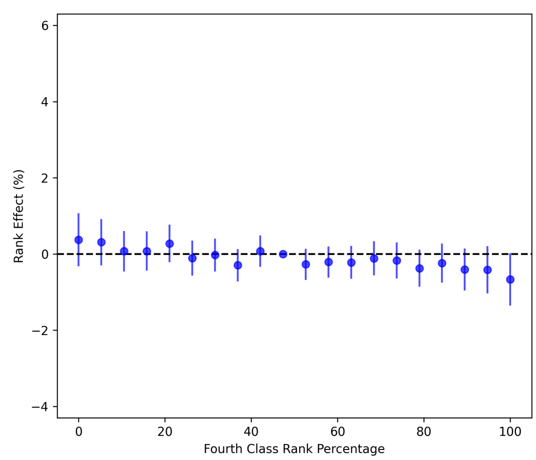
(a) Mental Health



(b) Learning Difficulty



(c) Physical Limitations



(d) Hearing Limitations

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of experiencing mental or physical difficulties later in life (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. The analysis is based on data from 187,830 students who completed the Census long form in 2021.

approximate 21% decrease in reported learning difficulties and a 12% decrease in mental health conditions.

Panel C and D highlight that these significant effects are largely confined to mental health and learning difficulties, showing no marked impact on hearing or physical impairments. This pattern indicates that the observed relationships are not driven by general health differences but are instead specific to the psychological and cognitive domains most likely to be affected by early academic standing.

For Figure 3, individuals were classified as having a condition if they reported experiencing it "sometimes." The main results remain largely robust if a stricter criterion is used—counting only those who report "often" or "always"—although effect sizes in percentage point diminish (see Figure 15 in the Annex). Moreover, while those questions were to targeted Canadian citizens aged 15 years or older, some younger respondents participated. Restricting the sample to only those older than 15 or even 18 years (the legal age) does not alter the magnitude or statistical significance of the findings (see Figure 16 in the Annex). Table 4 summarizes the impact of rank by analyzing it's impact for variations in rank that happen often in the data. Again we observe that most of the impact occurs at the extreme of the rank distribution.

Table 4: Impact of Fourth Rank Shifts on the Likelihood of Future Health Issues and Learning Difficulties

Long Term Difficulties	**0–5% → 10–15%**	**25–30% → 45–50%**	**50–55% → 70–75%**	**85–90% → 95–100%**
Mental Health Condition	-11.50***	-2.58	3.15	-2.27
Learning Difficulty	-20.83***	-8.02*	-1.74	-7.52*

Notes: Each column shows the estimated change (in percentage) in the likelihood of receiving the listed diagnosis in 4th grade when a student's rank shifts from the lower to the higher percentile band specified in the column header. These estimates are calculated from differences in the relevant coefficients in Equation 2, with statistical significance assessed via F-tests. For example, the first column indicates how the probability of being diagnosed changes when a student's rank moves from the 0–5% to the 10–15% band. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The analysis is based on data from 187,830 students who completed the Census long form in 2021.

4.3 Heterogeneous Effects Across Academic Subjects

This section relaxes the assumption that the impact of rank is uniform across topics, instead exploring which specific rankings are most influential for teachers' diagnostics and which significantly affect student outcomes. To this end, the analysis focuses on the effects of individual ranks in Numeracy, Reading, and Writing, rather than aggregating them into a combined rank using estimating equation 3.

Analysis of subject-specific rank effects reveals distinct patterns across different diagnoses (Figure 17 in the appendix). Writing rank emerges as the primary driver of learning difficulty and mental health diagnoses, while Mathematics rank plays a decisive role in gifted identification. In contrast, Reading rank appears less salient and is generally insignificant for all diagnoses. The strong influence of Math rank on gifted classification likely stems from the perception that mathematical proficiency signals higher cognitive ability and future success—a view supported by evidence linking math skills to individual earnings and economic growth (Hanushek and Woessmann, 2012). Furthermore, this analysis highlights a key limitation of aggregating ranks across subjects: by combining them, the distinct effects of each subject's rank become obscured, potentially leading to an underestimation of overall rank importance when certain subjects have little or no effect.

4.4 Heterogeneity

In this section I am investigating how the impact of rank varies across different demographic groups. For this purpose, I am separately estimating model (2) for each group. My analysis examines heterogeneity in the 4 main outcomes: Gifted Diagnosis, Learning Disability (diagnosis), mental health and difficulty learning. It is important to note that the samples are not balanced, as fewer cohorts are considered for the Census outcomes. Figure 16 displays the results of the heterogeneity analysis by gender.

Although there are minor differences in the magnitude of the estimated coefficients for certain outcomes, the overall patterns are broadly similar between male and female students, making it difficult to draw strong conclusions about meaningful gender differences. Heterogeneity analyses for other subgroups—such as minorities and low- versus high-income students—are found in Figures 17, and 18 in the Appendix. While some variation emerges, the general direction and significance of the rank effects remain consistent across these groups, suggesting that any subgroup differences are relatively modest in scale.

Given the lack of pronounced differences in these diagnosis outcomes by demographic subgroups, it appears that any teacher bias affecting diagnoses is not systematically stronger for one group than another. Instead, rank-based assessments appear to uniformly influence teacher decisions, rather than selectively targeting specific demographics.

4.5 Robustness Checks

Lacking specific classroom indicators, I used rank data across the entire school cohort. To ensure the robustness of the results, I re-estimated the model using only cohorts with fewer than 30 students—likely representing individual classrooms. Figure 12 presents the results for our main outcomes. Reassuringly, the magnitudes of the estimates are consistent with the broader analysis. However, the standard deviations are larger, which is expected given the smaller sample size.

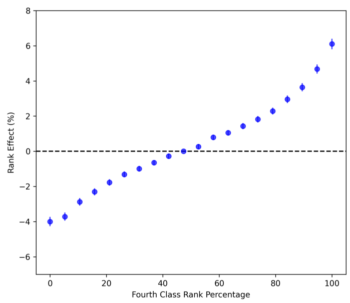
To test the robustness of my findings, I examine how different functional form assumptions about the relationship between ability and outcomes affect the results. Figure 13 in the annex presents estimates using alternative specifications that relax the non-linear ability hypothesis. The results remain qualitatively similar across these different functional forms, suggesting that the findings are not driven by biases of the baseline specification.

4.6 Impact of Early Academic Rank on Academic Success and Labour Market Outcomes

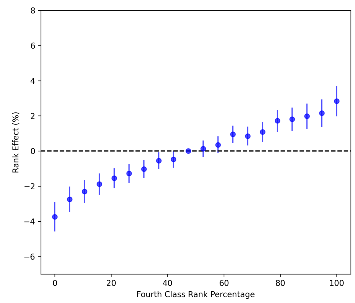
To validate the robustness of my findings, I analyze how fourth-grade academic rank influences subsequent academic and labor market outcomes, enabling comparison with existing literature. Figure 6 presents these results.

The results underscore the significant influence of early academic rank on future performance, including grades, high school completion, bachelor's degree enrollment, STEM enrollment, and income. Importantly, the magnitude and patterns align closely with those reported in related studies, particularly Denning et al. (2023), which investigated third-grade rank impacts in the U.S. For instance, moving from the 50th-55th to the 75th-80th percentile in fourth-grade rank yields a 2 percentage point increase in seventh-grade test scores, comparable to their finding of a 2.5 percentage point gain in eighth-grade scores. Similarly, advancing from the 25th to 75th percentile in

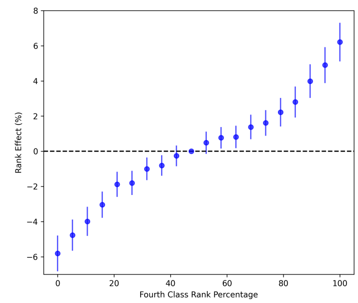
Figure 5: Impact of Fourth-Year Rank on Academic Success and Labour Market Outcomes



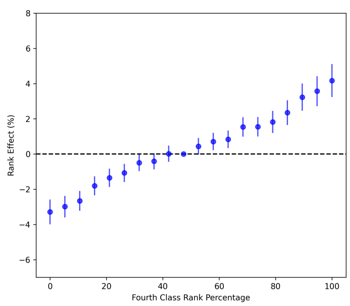
(a) Average Score 7th Grade



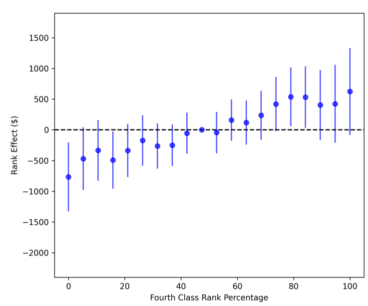
(b) Completing High School



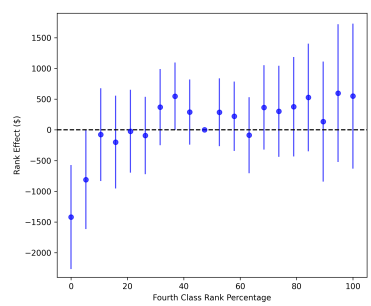
(c) Bachelor Enrollment



(d) STEM Enrollment



(e) Income 24



(f) Income 26

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on labour and academic success later in life. Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. The sample size varies across panels depending on how long each student could be tracked in the data.

rank increases high school graduation probability by 3 percentage points and bachelor's enrollment by 4 percentage points, while they find 4 percentage points for both outcomes. This consistency across different educational systems not only validates my findings but also suggests that relative academic rank exerts similar influences on long-term outcomes regardless of institutional context.

5 Conclusion

In this study, I provide evidence that primary school rank significantly impacts learning confidence, mental health conditions, and diagnostic outcomes into adulthood. Specifically, moving from the bottom 5% of the classroom rank to the 10–15% range reduces the probability of experiencing learning difficulties and mental health problems in adulthood by 21% and 12%, respectively. These findings underscore the profound and lasting influence of early academic rank on individuals' psychological trajectories.

Furthermore, this study provides robust evidence that early academic rank significantly influences diagnostic outcomes. Specifically, moving from the bottom 5% of the classroom rank to the 10–15% range reduces the likelihood of being diagnosed with a learning disability by 34% and with a mental health condition by 16%. Conversely, moving from near the top (85–90%) to the very top (95–100%) of the rank distribution increases the probability of a gifted diagnosis by 27%. Moreover, the analysis yields consistent results when examining the influence of 7th-year academic rank on 7th-year educational diagnoses.

Critically, these results hold even after accounting for parental feedback, suggesting that the observed effects primarily stem from institutional and teacher responses to academic rank rather than parental influence. This underscores the central role of classroom ranking in shaping teachers' perceptions and diagnostic decisions.

Subject-specific classroom rankings significantly shape diagnostic outcomes: numeracy rank exerts a pronounced effect on gifted designations, whereas lower writing ranks are strongly associated with both learning and mental health diagnoses. The findings are consistent to a series of robustness checks—examining different cohorts, grade levels, and functional forms—underscoring that rank-induced perceptions form early and profoundly shape how teachers and institutions identify, label, and support students.

In summary, these findings carry significant implications for educational policy and practice. They underscore the necessity for teacher training programs that address implicit biases and advocate for more holistic, objective assessment methods. Universal testing, for instance, can provide standardized and objective measures of student abilities, reducing reliance on relative rankings and mitigating potential biases. to ensure fair and equitable support for all students.

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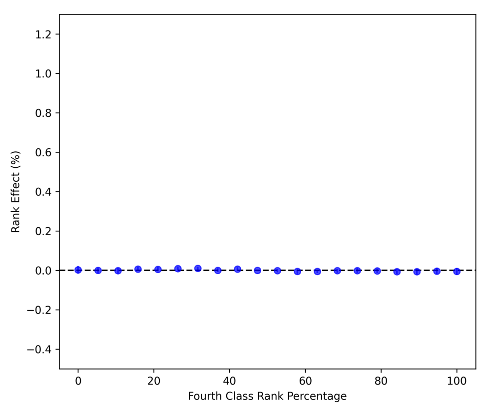
6 Annex

Table 5: FSA participation per year

Year	Freq.	Percent	Cum.
2000-2001	89,500	10.84	10.84
2002-2003	85,900	10.40	21.24
2004-2005	82,400	9.97	31.21
2006-2007	78,200	9.46	40.67
2008-2009	71,000	8.59	49.27
2010-2011	71,300	8.63	57.91
2012-2013	72,300	8.75	66.65
2014-2015	69,700	8.44	75.09
2016-2017	70,400	8.52	83.61
2018-2019	69,400	8.40	92.01
2020-2021	66,000	8.00	100.00
Total	826,100	100.00	

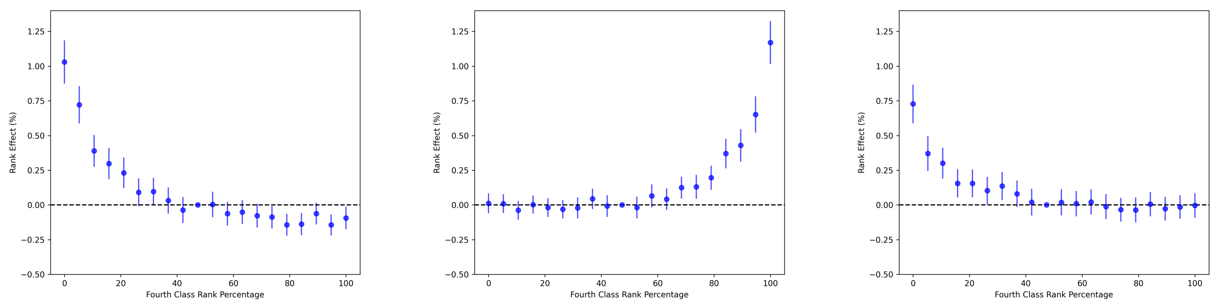
This table indicates the number of students who participated in the FSA across various years.

Figure 6: Impact of Fourth-Year Academic Rank on blind diagnosis



This figure depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving a blind diagnosis in fourth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

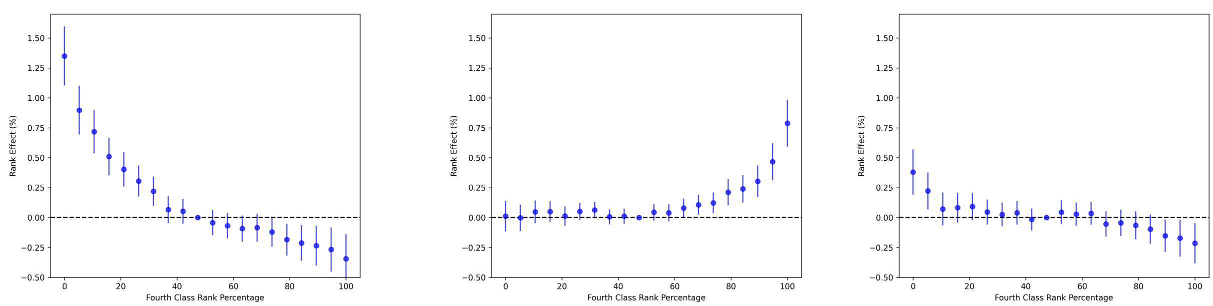
Figure 7: Effect of Seventh-Grade Academic Rank on Diagnostic Outcomes in Seventh Grade



(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

These figures depict the estimated effect of seventh-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in seventh-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

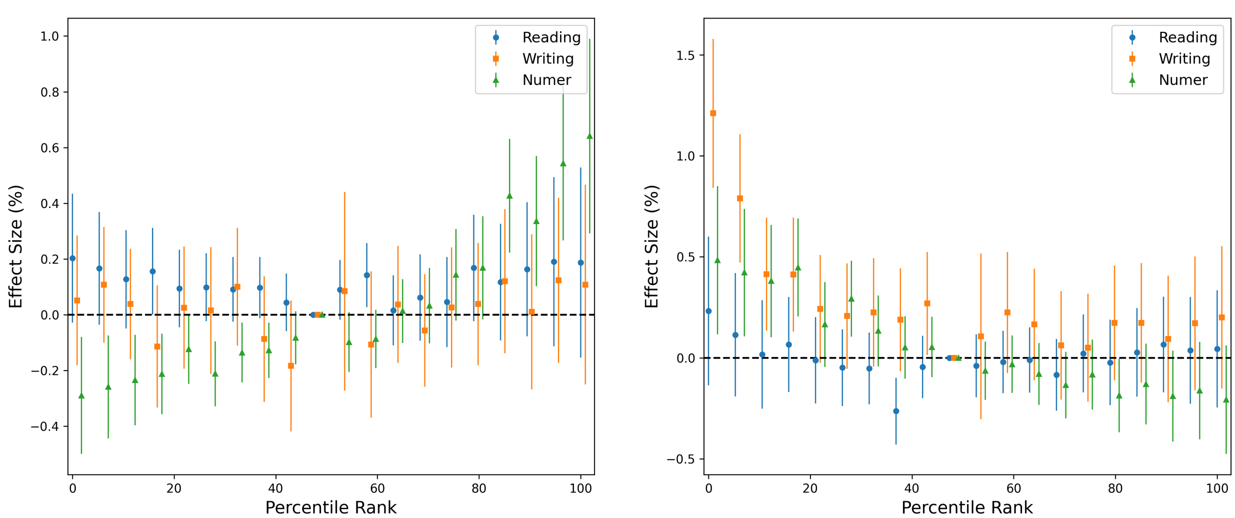
Figure 8: Effect of Fourth-Grade Academic Rank on Diagnostic Outcomes in Fifth Grade



(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

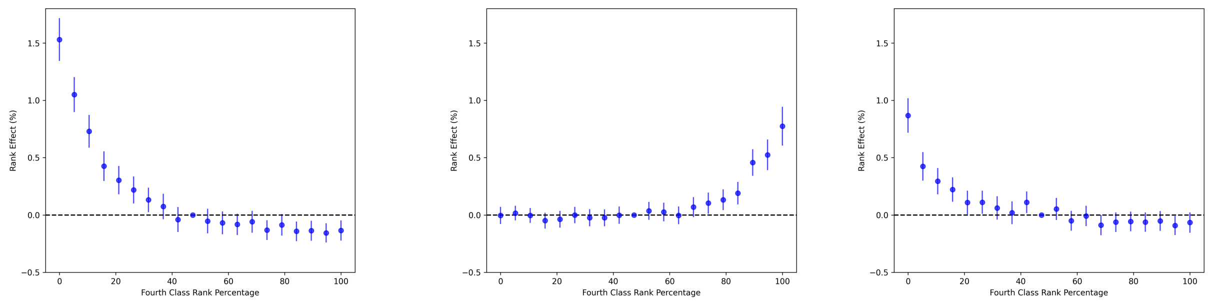
These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in fifth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

Figure 17: Full Model for learning trouble and Gifted diagnosis



These figures depict the estimated effect of fourth-year rank by topic—measured in ventiles—on the likelihood of being diagnosed as gifted or with learning disabilities in 4th grade. Estimates come from Equation (3) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

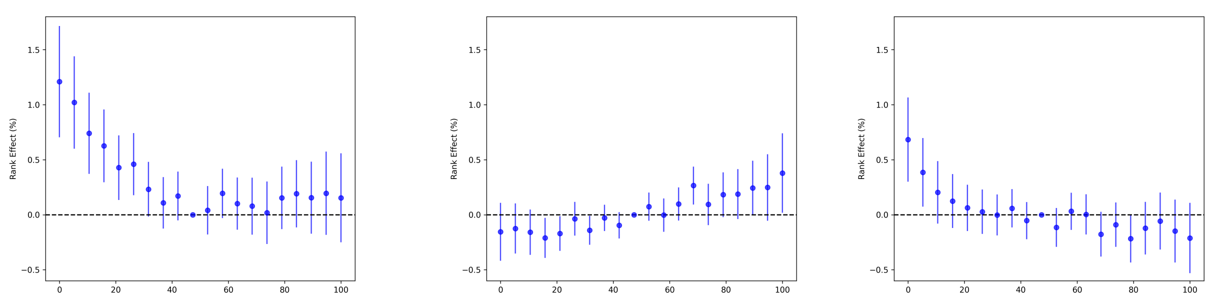
Figure 9: Effect of Seventh-Grade Academic Rank on Diagnostic Outcomes in Eighth Grade



(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

These figures depict the estimated effect of seventh-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in eighth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

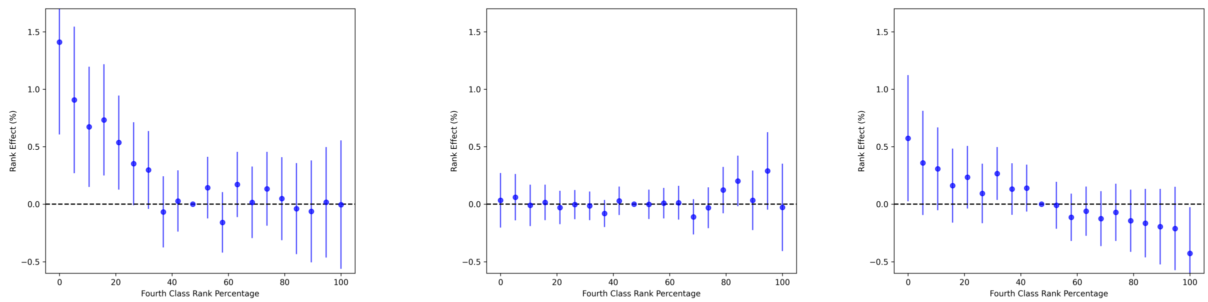
Figure 10: Effect of Fourth-Grade Academic Rank on Diagnostic Outcomes in Fourth Grade (2017+)



(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in fourth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. These results are derived exclusively from students who took the FSA starting in 2017 and later.

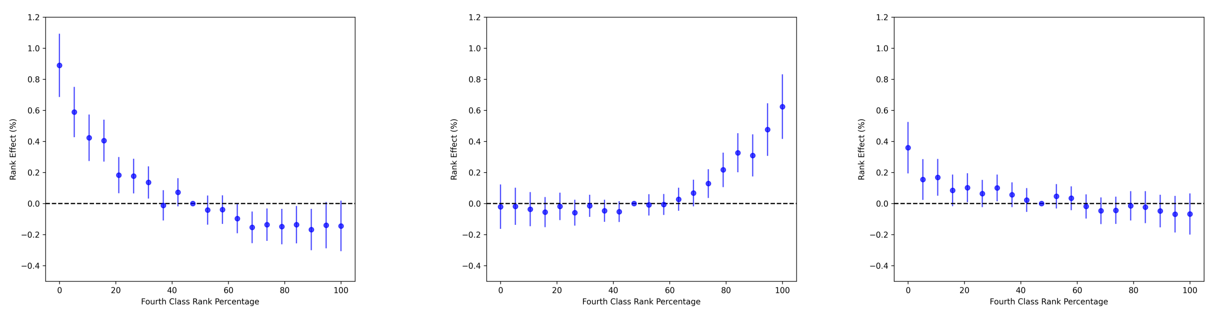
Figure 11: Effect of Seventh-Grade Academic Rank on Diagnostic Outcomes in Seventh Grade (2017+)



(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

These figures depict the estimated effect of seventh-year rank—measured in ventiles—on the probability of receiving certain educational diagnoses in seventh-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. These results are derived exclusively from students who took the FSA starting in 2017 and later.

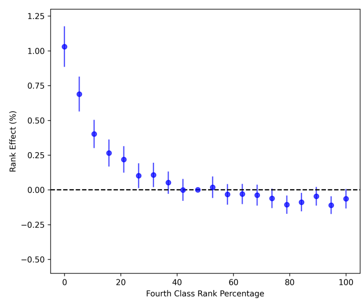
Figure 12: Effect of Fourth-Grade Academic Rank on New Diagnostic Outcomes in Fourth Grade



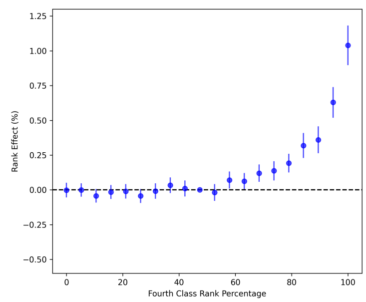
(a) Learning Disability Diagnosis (b) Gifted Diagnosis (c) Mental Health Diagnosis

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving a new educational diagnoses in fourth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

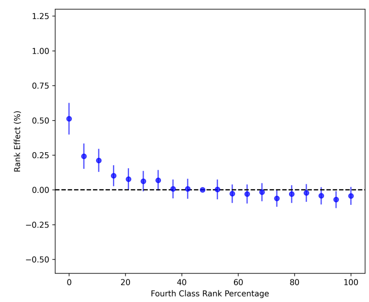
Figure 13: Effect of Seventh-Grade Academic Rank on New Diagnostic Outcomes in Seventh Grade



(a) Learning Disability Diagnosis



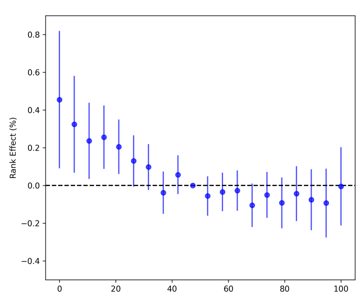
(b) Gifted Diagnosis



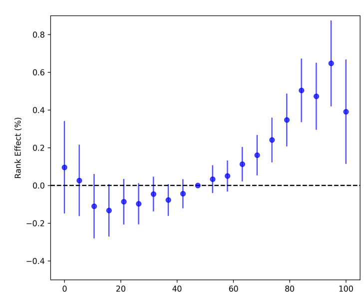
(c) Mental Health Diagnosis

These figures depict the estimated effect of seventh-year rank—measured in ventiles—on the probability of receiving a new educational diagnoses in seventh-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

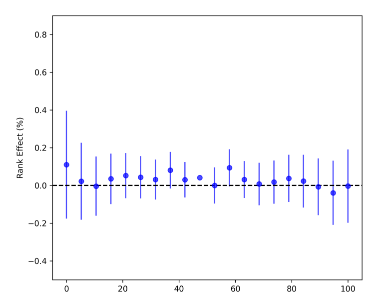
Figure 14: Effect of Fourth-Grade Academic Rank on Diagnostic Outcomes for "On Track" students



(a) Learning Disability Diagnosis



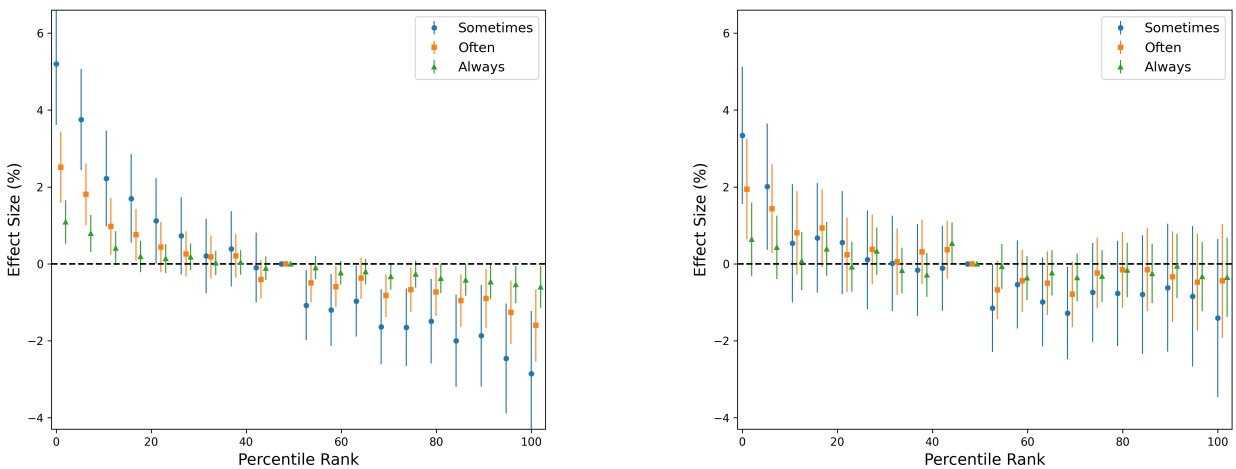
(b) Gifted Diagnosis



(c) Mental Health Diagnosis

These figures depict the estimated effect of fourt-year rank—measured in ventiles—on the probability of receiving a new educational diagnoses in seventh-grade (in percentage points) conditional on being in the "On Track" category. Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance.

Figure 15: Impact of Fourth-Year Academic Rank on Long-Term Mental Health and Learning Difficulties: Robustness Check Varying Severity

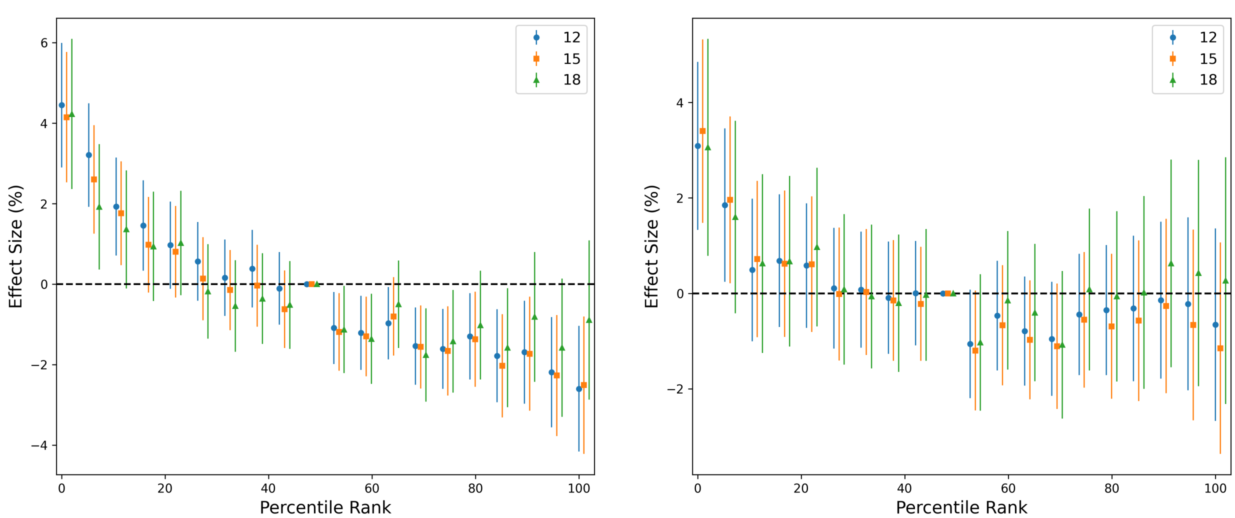


(a) Learning Difficulty

(b) Mental Health

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of experiencing mental difficulties later in life, with results expressed in percentage points. I adjust the criteria for being affected by a condition, varying it from "sometimes" to "often" and finally to "always."Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. The analysis is based on data from 187,830 students who completed the Census long form in 2021.

Figure 16: Impact of Fourth-Year Academic Rank on Long-Term Mental Health and Learning Difficulties: Robustness Check With Varying Age Thresholds

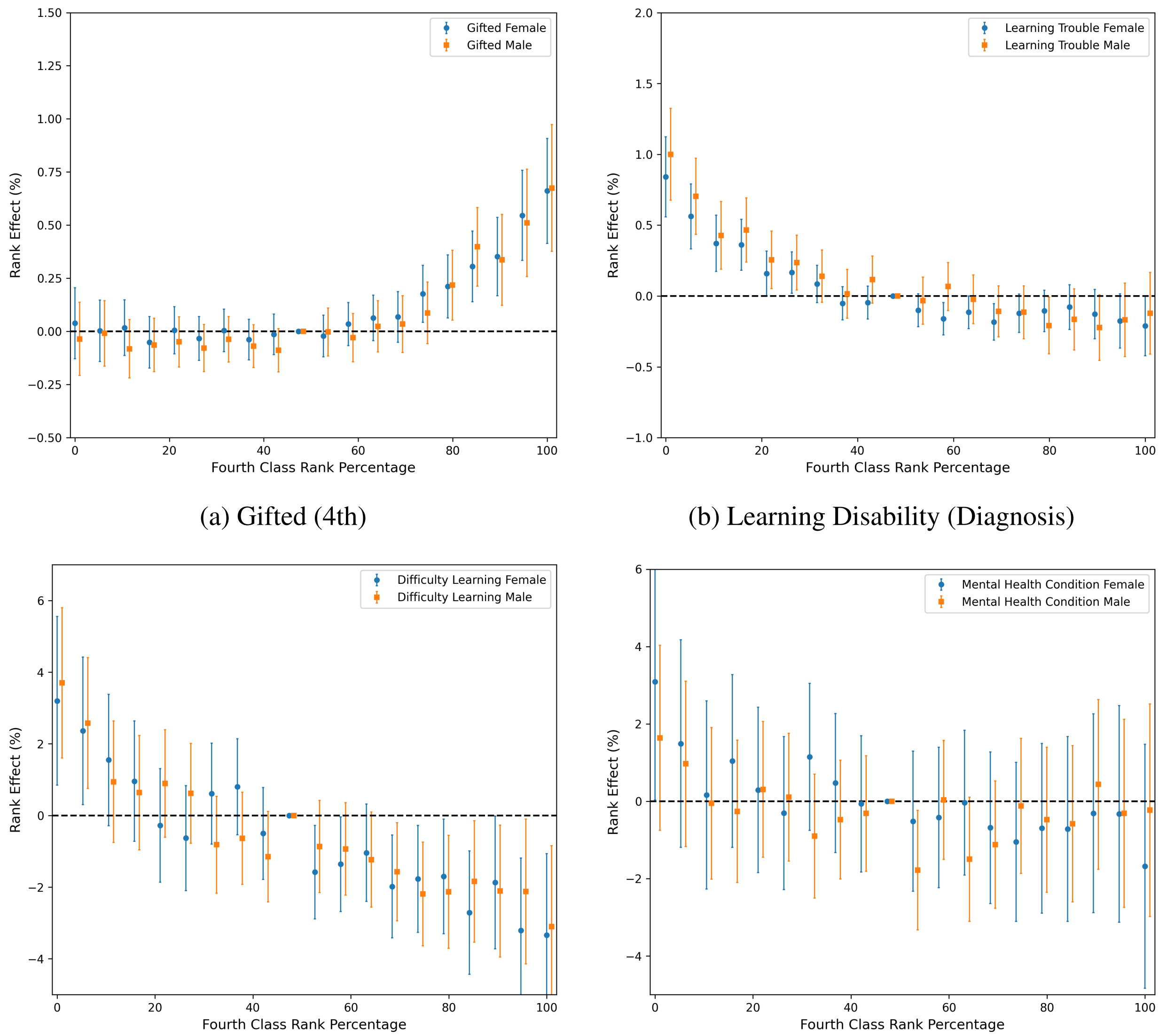


(a) Learning Difficulty

(b) Mental Health

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of experiencing mental difficulties later in life, with results expressed in percentage points."Estimates come from Equation (2) with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. The analysis is based on data from 187,830 students who completed the Census long form in 2021, I vary the minimum age the individual needs to have when answering the Census.

Figure 18: Gender-Specific Impacts of Fourth-Year Rank on Academic Diagnoses, Mental Health, and Long-Term Learning Outcomes



(a) Gifted (4th)

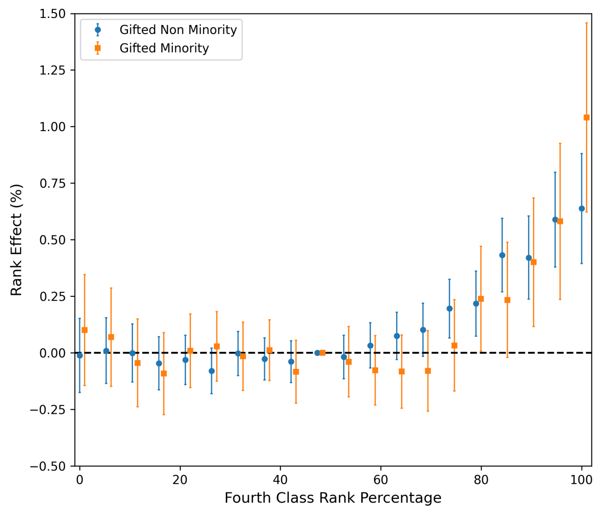
(b) Learning Disability (Diagnosis)

(c) Difficulty Learning

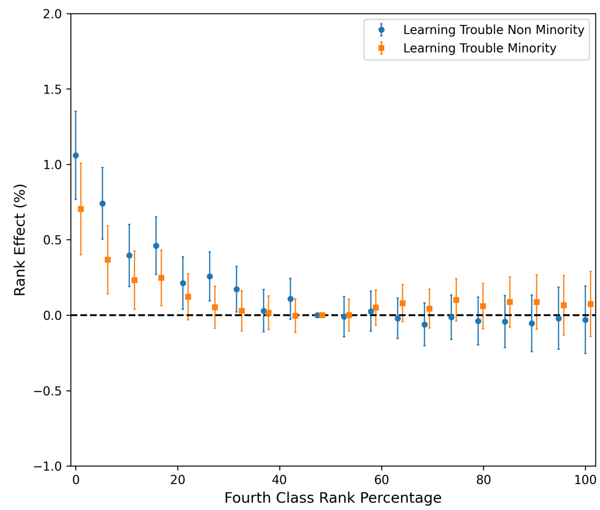
(d) Mental Health

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving certain diagnoses in fourth-grade and mental health difficulties later in life (in percentage points). Estimates come from Equation (2) estimated separately by gender with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. For Panel C and D only 187,830 students who completed the Census long form in 2021 are used.

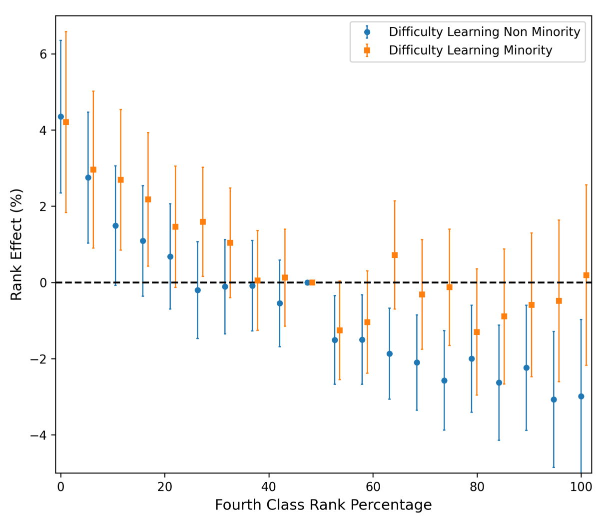
Figure 19: Differential Effects of Fourth-Year Rank by Minority Status on Academic Diagnoses, Mental Health, and Long-Term Learning Outcomes



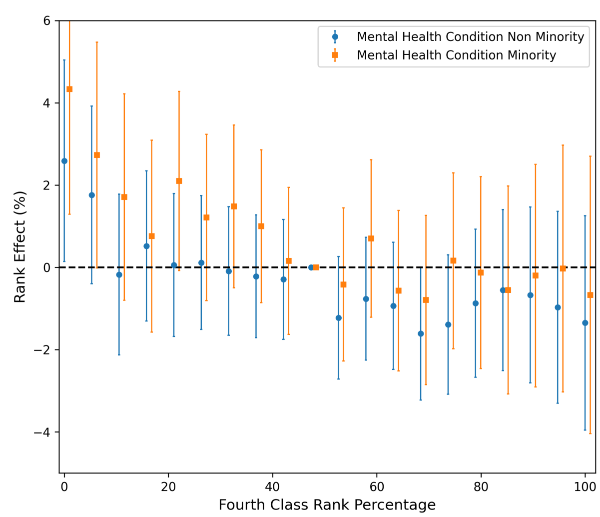
(a) Gifted



(b) Learning Difficulty (Diagnosis)



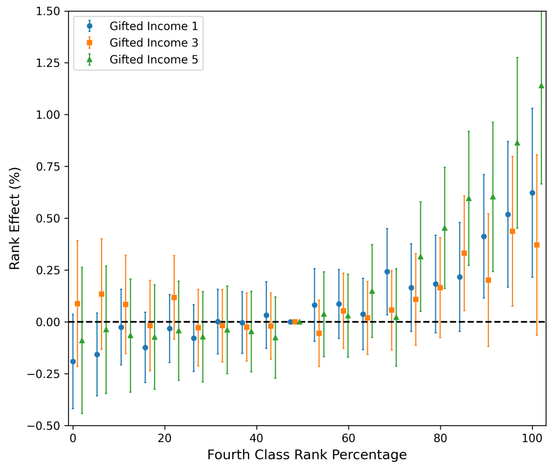
(c) Difficulty Learning



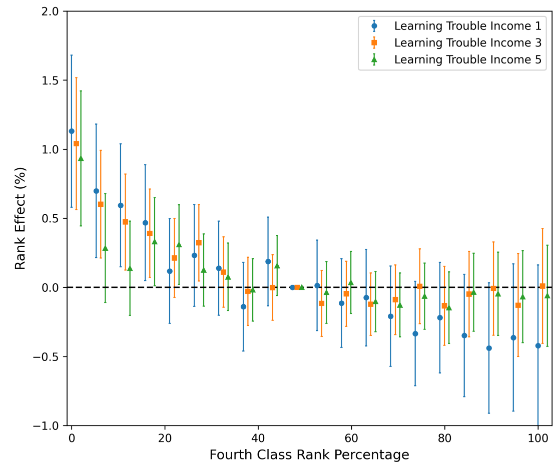
(d) Mental Health

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of certain fourth-grade diagnoses and mental health difficulties later in life (in percentage points). Estimates come from Equation (2) estimated separately by minority staty with 95% confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. For Panel C and D only 187,830 students who completed the Census long form in 2021 are used.

Figure 20: Differential Effects of Fourth-Year Rank by Parental Income on Academic Diagnoses, Mental Health, and Long-Term Learning Outcomes



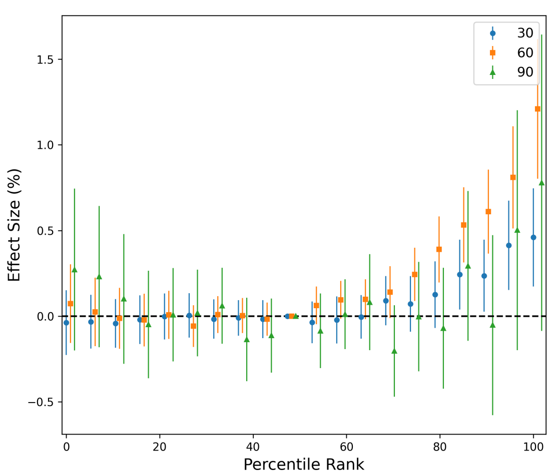
(a) Gifted



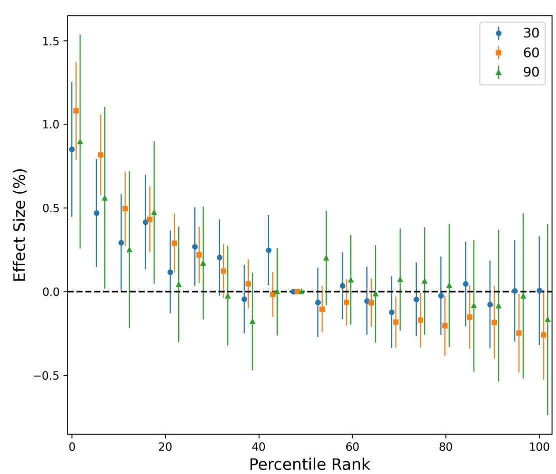
(b) Learning Difficulty (Diagnosis)

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of certain fourth-grade diagnoses (in percentage points). Estimates come from Equation (2) estimated separately by parental income with 95confidence intervals, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. (The results for mental health are not precisely estimated because of the small sample size)

Figure 21: Differential Effects of Fourth-Year Rank by Classrooms sizes on Academic Diagnoses, Mental Health, and Long-Term Learning Outcomes



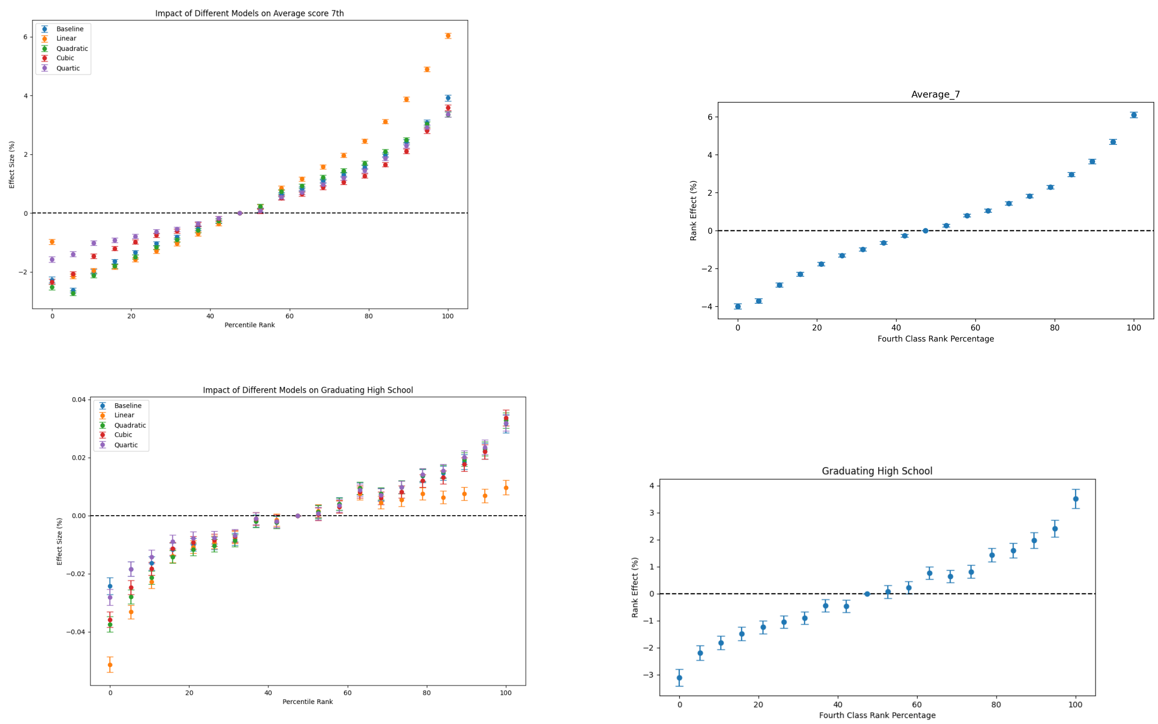
(a) Gifted



(b) Learning Difficulty (Diagnosis)

These figures depict the estimated effect of fourth-year rank—measured in ventiles—on the probability of receiving a new educational diagnoses in fourth-grade (in percentage points). Estimates come from Equation (2) with 95% confidence intervals, estimated separately by cohort size, using school-cohort clustered standard errors. The 45th-50th percentile serves as the reference group. The model controls for minority status, gender, parental income, and includes student ability indicators (in ventiles) interacted with (SSC) test score distributions, with (SSC) grouped into 25 categories based on mean and variance. (The results for mental health are not precisely estimated because of the small sample size)

Figure 22: Robustness checks for different ability functional form



These figures display the coefficients for the impact of 4th-grade rankings by ventile, accompanied by their 95% confidence intervals, on various outcomes: 7th-grade performance and the likelihood of completing high school. On the left, the results are derived from Equation 2 with a non-linear model of ability impact. On the right, the results are from the same equation but with a specified functional form imposed on the ability, replacing the non-linear model.