NBER WORKING PAPER SERIES

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Working Paper 33282
http://www.nber.org/papers/w33282

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2024, Revised May 2026

We are extremely grateful to Cynthia Park for assistance in accessing and interpreting the data used in this study as well as information about the District's policies and practices, and to Tatiana Reyes for extraordinary research assistance. We also thank seminar participants at Brigham Young University, Duke University, McGill University, Queen's University, RWI Essen, Simon Frazer University, UC Merced, UC Riverside, UC Santa Barbara, University of Nevada-Las Vegas, University of Utah, University of Virginia, and the Upjohn Institute. The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through grant R305C200012 to the National Center for Research on Gifted Education. The opinions expressed are those of the authors and do not represent views of the U.S. Department of Education or the National Bureau of Economic Research.

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NBER Working Paper No. 33282
December 2024, Revised May 2026
JEL No. I21, I24

ABSTRACT

Boys are less likely than girls to enter college, a gap often attributed to differences in noncognitive skills. We study how being classified as gifted – determined by having an IQ score of 116 – affects college entry for disadvantaged children in a large urban school district. We find increases of around 50 percent for marginally eligible boys, but only small effects for girls. There are also large effects for boys (but not girls) on course-taking and grades in middle and high school with no effects on standardized tests scores. These patterns suggest that gifted services raise the non-cognitive skills of underachieving boys, leading to gains in educational attainment.

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Boys are less likely to enter college than girls (Jacob, 2002; Goldin et al., 2006). The gap is concentrated among children from disadvantaged backgrounds: recent data from the Postsecondary Student Aid Study show that the ratio of males to females among college freshmen is close to 1 for children from the top income quartile, but falls to only about 60% for children from the bottom quartile (see Appendix Figure A1).[1] Even more striking is the gender gap among children from disadvantaged backgrounds with higher cognitive ability. Figure 1 shows college entry rates by gender and participation in the free- and reduced-price lunch (FRL) program for children with differing levels of cognitive ability, as measured by IQ and standardized tests in second grade.[2] At low levels of cognitive ability, the differences between the four groups are small. But at higher levels, low-income boys lag far behind the other groups.

What is going wrong for these boys? Jacob (2002) and Becker et al. (2010) argue that the gender gap in college entry arises from boys' lack of *non-cognitive* skills like motivation and self-discipline and show that controlling for proxies of these skills can explain most of the difference between girls and boys. Likewise, Heckman and Rubinstein (2001) and Heckman et al. (2006) argue that socioeconomic gaps in schooling attainment are driven in large part by the under-development of non-cognitive skills. Indeed, the model estimated by Heckman et al. (2006, Figure 21) shows that higher cognitive skills have little effect on college completion rates unless they are accompanied by higher non-cognitive skills. These two strands of work suggest that disadvantaged boys face a *double penalty* in non-cognitive skill formation that is especially important for those with higher cognitive skills.

There is less evidence on whether K-12 education policies can improve non-cognitive skills and help close the gender gap in college entry. Jackson (2018) shows that certain 9th-grade teachers can increase non-cognitive skills and boost high school completion rates; Petek and Pope (2023) find similar results that extend to teachers of younger children. However, neither study compares girls and boys. Rose et al. (2022) show that exposure to teachers who raise

[1] Many recent papers have emphasized the problems faced by boys from disadvantaged backgrounds. See, for example, Bertrand and Pan (2013) Chetty et al. (2016) and Autor et al. (2019).

[2] These data are from the school district we study and include children who were in 2nd grade in 2008-2010. We measure disadvantaged status by participation in the free or reduced-price lunch (FRL) program. We measure cognitive ability by a combination of math and reading scores on the 2nd-grade SAT test and the Naglieri Non-verbal Ability Test (an IQ-like test used in the district to screen for gifted children) and scale ability by the predicted college entry rate of non-disadvantaged girls. There are only small mean differences by gender in the distributions of ability, though boys have somewhat fatter tails than girls. Goldin et al. (2006) report that distributions of IQ among high school juniors in the Wisconsin Longitudinal Survey are almost identical for boys and girls.

student attendance and other measures of non-cognitive skill lowers subsequent criminality, with similar effects for girls and boys. In a randomized intervention aimed at higher-ability children in Italy, Carlana et al. (2022) find that a middle school tutoring and counseling program raises the fraction of high-achieving immigrant boys who choose an academic high school track, closing the gap with their female counterparts.[3]

A long-established constellation of gifted programs in the U.S. – serving about 3 million students per year – is designed in part to ensure that children with high cognitive abilities remain engaged in school and progress to college (VanTassel-Baska, 2018; Siegle and McCoach 2005).[4] In this paper, we study the effects of being identified as gifted in elementary school on subsequent test scores, courses and grades, and on the probability of entering college, for disadvantaged children in a large urban school district (hereafter, "the District").[5] To qualify for gifted status in the District, English language learners (ELL's) and FRL participants must have an IQ score of 116 points or higher (roughly the 84th percentile in the national distribution). This comparatively generous eligibility standard, coupled with a universal screening program to identify higher-ability students, means that the District serves a relatively large number of disadvantaged students in its gifted program. The strict IQ threshold for gifted status also provides the basis for a regression discontinuity (RD) evaluation of the impacts of gifted identification.[6]

Focusing on ELL/FRL students who had a first IQ test by the end of 5th grade, scored 106-124 points, and remained in the District for 7 more years – a sample of about 3,500 students – we show there is a large discontinuity in the probability of being classified as gifted at the 116-

[3] Broadly consistent with the results, though operating at a much later stage, Canaan, Fischer, Mouganie & Schnorr (2024) find that a low-touch counseling intervention for college students on probation leads to improvements in GPA, completion, and earnings – with benefits concentrated among low-SES students, males, and STEM majors.
[4] The literature on gifted education has long been concerned with gifted "underachievement," which has been linked to low motivation/self-regulation and negative perceptions of school (White et al. 2018) and is more prevalent among boys than girls (Reis and McCoach 2000; Matthews and McBee 2007). However, only a handful of studies examine the causal effects of gifted programs. Bui et al. (2014) study the impacts of gifted status on test scores and, as in our study, find no significant effects (see below for further discussion).
[5] Our data sharing agreement with the District requires that it is not specifically identified. The District is located in Florida.
[6] Non-disadvantaged students face an IQ eligibility threshold of 130 points. Results available on request suggest that gifted identification has no significant impact on college entry for these students, though as noted by Card and Giuliano (2014), there is substantial manipulation of IQ scores around the 130-point threshold.

point threshold.[7] Once identified, gifted students retain their status through the end of high school and receive a package of services in subsequent years. These include a state-mandated Education Plan (EP) specifying instructional goals, and biannual meetings to review students' progress and identify options at key transition points.[8] In addition, gifted students in the District are assigned to separate gifted/high achiever (GHA) classrooms for 4th and 5th grades and can receive higher priority for advanced-track courses in later grades, particularly in middle school.

We evaluate the impacts of gifted status by 5th grade on college entry 7 years later (i.e., "on time") and on a wide range of intermediate outcomes in elementary, middle and high-school. A concern for our analysis is that psychologists have some discretion in scoring IQ tests, leading to bunching at the threshold for gifted eligibility. We address this with a standard "donut RD" approach (Barreca et al., 2011).[9] To assess the robustness of our results, we present RD estimates using a range of bandwidths for all outcomes and summarize the impacts on college entry using a two-dimensional grid of bandwidths to the right and left of the IQ cutoff.

Our main finding is that for disadvantaged boys with IQ's near the 116-point cutoff, being identified as gifted leads to a large increase in the probability of completing high school on time and entering college the following year. Estimates from our preferred specification imply a 28 percentage point (ppt) increase in on-time college entry, from just under 50% for those who narrowly miss gifted status to around 75% for those who meet the threshold – comparable to the rate for similar-IQ girls with scores just under the threshold. In contrast, we find relatively small, statistically insignificant effects (~5 ppt) on the college entry rate of girls. While the point estimates vary with bandwidth choices, even the most conservative estimates for boys imply marginally significant effects of around 10 ppt, while the estimates for girls are nearly always smaller than this.

We go on to explore the effects of gifted status on a wide range of intermediate outcomes, using detailed information on course selections, course grades, and standardized test scores. We find no effects on statewide standardized test scores or on PSAT scores for either

[7] Nearly all students who are ever classified as gifted in the District have an IQ test by the end of 5th grade, and ~80% are IQ-tested before 4th grade. We include those tested in grades 4 and 5 to increase our sample size. We focus on students who remain in the District until the nominal high school completion time so that we can measure their middle and high school outcomes and college attendance. As discussed below, we find no evidence of a discontinuity in the probability of remaining in the District.
[8] EP's – which are analogous to the plans developed for Special Needs children – are a central feature of gifted programming in most states (Zirkel, 2005).
[9] We also use only the first reported IQ score to avoid concerns about selective re-testing.

boys *or* girls, suggesting that gifted services have little or no impact on cognitive skills. Looking at outcomes that are widely interpreted as markers of non-cognitive skill, however, we find large positive effects for boys. Specifically, we find a 25-ppt increase in the probability that boys enter an accelerated math program in 6th grade, a nearly 30-ppt increase in the probability of completing Algebra 1 before 9th grade, and a doubling of the number of AP classes taken in high school. We also measure a 0.4-point increase in average grades in high school math (on a standard 4-point scale), and relatively large impacts on the pre-high school test scores of classroom peers – indicating that gifted boys are more likely to take advanced-level classes.

In all these domains, passing the gifted threshold allows boys to catch up (or nearly catch up) to girls with similar IQ's, whereas there is little or no effect for girls. We offer a suggestive explanation for this pattern, based on the hypotheses that cognitive and non-cognitive skills are complementary inputs in the education production function (e.g., Heckman et al. 2006), and that gifted services raise non-cognitive skills with little or no effect on cognitive skills. A gain in non-cognitive inputs is particularly impactful for disadvantaged boys with higher IQ's, assuming that the reason for their "underperformance" in school is low non-cognitive skills relative to their cognitive skills. Our results suggest that gifted services raise their non-cognitive skills to levels comparable to those of girls with similar IQ scores, leading to increased engagement in middle and high school and higher college entry rates. In contrast, we conjecture that even in the absence of gifted services, most girls have non-cognitive skills that are aligned with their cognitive skills. In such a case, a boost in non-cognitive skills with no change in cognitive skills will have relatively little impact on longer term educational outcomes.

We provide some evidence for this explanation using an available measure of non-cognitive skill for students in third grade based on their responses to a survey question on how much they enjoy school.[10] For children of both genders with a higher indicator of non-cognitive skill, we find small effects of gifted status on college entry. For children with a lower indicator, however, we find larger positive treatment effects of gifted status – suggesting that these services are valuable for students of either gender who were less engaged with schooling in early elementary grades.

[10] As discussed below, most gifted students are identified in 3rd grade and receive some limited services in that grade, but we believe the impact of these services is small, so we think of this question as reflecting the student's engagement in school prior to any significant gifted services. Unfortunately, we do not observe course grades (the most widely used indicator of non-cognitive skills) prior to middle school.

Our paper contributes to four distinct literatures. The first is a body of work addressing the gender gap in college entry/completion (e.g., Jacob, 2002; Charles and Luoh, 2003; Goldin et al., 2006; Vincent-Lancrin, 2008; Becker et al., 2010; Fortin et al., 2015). A second and related literature examines the interactions between family background and gender, noting that disadvantaged backgrounds are associated with particularly bad outcomes for boys (e.g., Bertrand and Pan, 2013; Chetty et al., 2016; Autor et al., 2019; Aucejo and James, 2019). Our work builds on both literatures, focusing on the gender gap in college entry for ELL and FRL children with relatively high cognitive ability. Like only a few previous studies – most notably, Carlana et al. (2022) – we contribute by studying the causal effects of a package of services that narrows the gender gap for higher-ability children from disadvantaged backgrounds.

A third, much smaller, literature analyzes the effects of gifted programming on student outcomes. Bui et al. (2014) and Card and Giuliano (2014) use RD designs based on gifted eligibility rules to examine impacts on standardized test scores 1-2 years after program entry. Like us, they find no significant impacts on test scores. Bui et al. (2014) also use a lottery design to study effects of being admitted to magnet schools, again finding no detectable effects on math or reading scores, but some gains in science.[11] Booij et al. (2016) and Lavy and Goldstein (2022) analyze high-school gifted programs in the Netherlands and Israel and find no effects on test scores or college entry (though college rates are already high in their samples).[12] We contribute to this literature by providing the first design-based study of the longer-term effects of gifted identification in a U.S. setting. Our focus on disadvantaged students around the 84th percentile of IQ's departs from most of the gifted education literature (see e.g., Subotnik et al., 2011), which focuses on children in the extreme upper tail of ability (i.e., the top 5% or even 1%).

Finally, our paper is related to a few other studies that look at advanced-track programs for high-achieving students in elementary grades.[13] Cohodes (2020) examines an accelerated curriculum program in 4th-6th grades for students who score highly on a 3rd-grade standardized exam and finds no effects on standardized test scores but a positive effect on college entry for

[11] An earlier study by Bhatt (2011) uses an instrumental variables approach and finds some evidence of a positive effect of being identified as gifted on test scores. As noted by Bui et al. (2014), her design is fragile. An unpublished study by Murphy (2009) also finds no systematic effects of gifted programs on test scores.
[12] Booij et al. (2016) find positive effects on course grades; Lavy and Goldstein (2022) find effects on double majoring and pursuing advanced degrees.
[13] More tangentially related are studies of selective high schools and high school tracks. Abdulkadiroglu et al. (2014) and Dobbie and Fryer (2014) find no effects of selective high schools in Boston and New York City on marginally eligible students.

Black and Hispanic students. She does not report results by gender. In previous work focused on advanced academic programs in the District, Card and Giuliano (2016b) examined the effects of assignment to GHA classrooms in grades 4-5 for non-gifted students. These students are selected based on their previous year's test scores to fill open seats in GHA classrooms at schools with too few gifted students. In contrast to the null effects on test scores for gifted students, Card and Giuliano (2016b) find positive effects for the non-gifted, high-achieving students that are concentrated among Blacks and Hispanics and significant for both boys and girls. A key distinction between our gifted program and test-based "tracking" programs studied elsewhere is the use of IQ scores to identify students as gifted. Indeed, many gifted students in our sample – especially those who just meet the 116 IQ threshold used for disadvantaged students – are far from the top of their class in test scores or grades.[14] Also, unlike the non-gifted high achievers studied by Card and Giuliano (2016b), gifted students in the District receive an EP and support services throughout their schooling careers.

The next section presents a simple model of educational attainment that emphasizes the complementarity of cognitive and non-cognitive skills and provides an interpretative framework for our empirical analysis. We then describe the District's gifted program and our data set, which combines student records from the District with college enrollment data from the National Student Clearinghouse. Next, we document the first-stage relationship between IQ scores and gifted status. We then turn to RD-based estimates of the effect of gifted status on our main outcome, on-time graduation and college entry, including an investigation into the differential effects by gender. We follow with an analysis of intermediate outcomes, focusing on patterns for boys versus girls and distinguishing between proxies for cognitive vs. non-cognitive skills. The final section of the paper offers an interpretation of our findings and their implications for policy.

[14] In Appendix Table A1, we present a side-by-side comparison of the compliers in our RD design for disadvantaged gifted students and the compliers in the RD design used in Card and Giuliano (2016b) for non-gifted high achievers. The two groups differ on several dimensions, including race/ethnicity, FRL status, neighborhood income, classroom composition, and baseline measures of cognitive and non-cognitive ability.

I. A Simple Framework

Heckman et al. (2006) propose an education production function in which schooling attainment (y) is related to two complementary inputs: cognitive ability (C) and non-cognitive inputs (N).[15] To simplify their model, we assume that:

$$y = \min[\, C \,,\; N \,] + u \qquad (1)$$

where u incorporates all other factors. The main attainment outcome in our empirical analysis is college entry, but we also look at a wide set of intermediate outcomes (like GPA and course completion rates in middle and high school), which we assume are produced in the same way. Our main measure of cognitive ability is IQ; we also observe test scores at different stages of school, which we interpret as (possibly noisy) measures of cognitive ability. We lack direct measures of non-cognitive skills, but we assume that the relevant non-cognitive input is itself a combination of various (potentially malleable) attributes A and a factor e representing student effort or engagement: $N = N(A, e)$. We further assume that students determine their effort by trading off their perceived benefits and costs of additional effort on school activities:

$$e = argmax\; \mu y - d(e; A),$$

where $\mu = \mu(A)$ represents the subjective value of higher attainment, and $d(e; A)$ represents the cost of effort, which we assume is strictly convex in effort. For example, we might think that μ is related to attributes like future-orientation (grit) and the desire to please parents and teachers (agreeableness), while attributes like self-discipline shift the marginal cost of effort.

Given our assumptions on (1), an optimal choice of effort (e^*) satisfies the first order condition:

$$\mu N_e(A, e^*) - d_e(e^*; A) = 0, \;\; N(A, e^*) < C$$
$$\mu N_e(A, e^*) - d_e(e^*; A) > 0, \;\; N(A, e^*) = C$$

For students of a given cognitive ability C who place a relatively high value on achievement or have a low marginal cost of effort, the choice of effort leads to a corner solution with $N = C$. Students who value schooling attainment less or have a higher cost of effort will

[15] There is a long history of education production function modeling in economics, starting with Bowles (1970). One strand of this literature focuses on teacher value added – see e.g., Hanushek (2020). Another addresses the effects of parental and other inputs in the production of skills, e.g., Todd and Wolpin (2003). A subset of the latter has considered both cognitive and non-cognitive skills and allowed for dynamic complementarities in the production of these skills (e.g., Cunha and Heckman 2008, Cunha, Heckman and Schennach 2010, Attanasio et al. 2020). Two key conclusions supported by these studies are that early childhood investments yield greater benefits than later remediation and that non-cognitive skills play an important role in making later investments more productive.

have an interior effort solution with $N < C$. These students could be characterized as "under-achievers" because they are not providing enough effort to raise their non-cognitive inputs up to the level of their cognitive ability.

In this setting, an education intervention can increase attainment by raising cognitive skills, or by raising non-cognitive inputs (either by inducing greater effort or by magnifying or redirecting effort). Here, we study the effects of gifted services on students with IQ scores (measured in early elementary grades) close to the gifted eligibility threshold. As we show below, these services have little or no effect on standardized test scores and PSAT scores, which we interpret as evidence that gifted services have no effect on cognitive skill. Under the assumptions of equation (1), this means that gifted services can increase attainment only by raising non-cognitive inputs among students for whom $N < C$ – i.e., those who were previously "under-performing" relative to their cognitive ability.

Such interventions might be expected to have different effects on girls and boys. Building on Jacob (2002) and Becker et al (2010), assume that in the absence of gifted services girls have non-cognitive skills that are closely aligned with their cognitive skills:

$$E[N(A, e^*)\ |C, girl, not\ gifted] = C,$$

reflecting relatively high levels of underlying non-cognitive attributes and higher (endogenously determined) effort, whereas boys with the same level of C have a relative deficit of non-cognitive skills:

$$E[N(A, e^*)\ |C, boy, not\ gifted]\ < C,$$

reflecting lower levels of A and lower levels of effort. In this case, even if gifted services lead to gender-neutral changes in the attributes affecting the choice of e, the effect on girls' educational attainment will be relatively small, while the effect on boys will be larger.

A useful extension of model (1) is to allow for different domains of attainment, cognitive skills, and effort. For example, let y_M and y_L be intermediate outcomes (e.g., average course grades) in math and language arts that are substitutes in the production of college enrollment. In turn, suppose each outcome y_D for $D \in \{M, L\}$ is related to domain-specific cognitive skills C_D and domain-specific non-cognitive skills $N_D(A, e_D)$ that depend on non-cognitive attributes and domain-specific effort. It is plausible that some students have relatively high cognitive skills in one domain (e.g., math), but fail to achieve at their "full potential" in that subject area (e.g., $N_M(A, e_M^*) < C_M$). In this scenario, an intervention that leads to greater effort in the math domain could have important and distinct effects on y_M. As we discuss below, disadvantaged boys who barely pass the IQ threshold for gifted status (i.e., the complying boys) have higher standardized test scores in math than in reading, and gifted services have relatively large impacts on their math-related outcomes in middle and high school. These findings suggest that for many boys, gifted services provide the boost in non-cognitive inputs they need to achieve outcomes consistent with their cognitive abilities in math.

As noted, our main outcome is on-time college entry, which we assume is determined by a combination of cognitive and non-cognitive skills in one or more subject domains. We also observe a wide set of intermediate outcomes, including subject-specific GPAs in high school and the number of AP courses completed by 12th grade. In prior studies of non-cognitive skills (e.g., Jackson 2018) and of gender gaps in these skills (e.g. Jacob 2002; Cornwell, Mustard and Van Parys 2013), observed outcomes like grades are interpreted as markers of non-cognitive skill *when cognitive skills are held constant*.[16] Since our regression discontinuity models condition on IQ – and since we find no evidence that gifted services affect test scores – we follow the literature and refer to outcomes like GPA and course selections as "measures" of non-cognitive skill, though in our framework they also reflect endogenous effort choices, which are determined in part by underlying attributes.[17] As we show below, we find generally similar treatment effects for course taking and GPA outcomes as for college entry – a pattern that is consistent with the hypotheses that there is strong complementarity between cognitive and non-cognitive skills and a non-cognitive skill deficit among boys that is partly remediated by gifted services.[18]

[16] This "task-based" approach to measuring non-cognitive skills is discussed at length by Heckman and Kautz (2014), who stress the importance of controlling for cognitive skills. Duckworth and Yeager (2015) compare task-based measures to direct measures using self-report and teacher-report questionnaires, while other studies (e.g., Cornwell et al. 2013 and Galla et al. 2019) directly link variation in self- and teacher-reported non-cognitive skills to variation in grades conditional on test scores.

[17] While several prior studies interpret grades or GPA as reflecting non-cognitive skills holding constant cognitive ability, we are not aware of any that use course selections. However, since grades tend to reflect the difficulty of a course in addition to cognitive and non-cognitive skills, we believe that it is important to examine both outcomes. We also recognize that students who maintain or improve their GPA while taking more challenging courses should be interpreted as putting forth greater effort. Notably, this interpretation is consistent with the common college admissions practice of assigning extra grade points to honors, AP, IB, and dual enrollment courses.

[18] A potential concern with attributing changes in our outcomes to changes in students' skills is that most of these outcomes could be affected directly by differential treatment of gifted students – e.g., teachers and counselors might be more forgiving of "bad behavior," push children into challenging classes, or provide additional assistance in the college application process. As such, the effects we measure could be mediated partly by behaviors that compensate for non-cognitive deficits rather than by improvements in non-cognitive skills.

II. Background and Data

The District is one of the 10 largest school districts in the country, serving around 20,000 students per grade. Its student body is racially diverse; about one-half are eligible for the FRL program. During our sample period, the District operated 140 larger elementary schools offering Kindergarten to 5th grade, 80 conventional middle schools offering grades 6-8, and 70 mainstream high schools. It also offered a wide variety of charter and special service schools. District policies for gifted students, including eligibility standards and services, are regulated by states laws and have been relatively stable since 2002, with some exceptions noted below.

a. Gifted Identification

Most gifted children in the District are identified between 2nd and 5th grades, with the modal student entering in 3rd grade (see Appendix Figure A2). Once identified, gifted students retain their status throughout their schooling careers through the end of high school. To be eligible for gifted status, state law requires students to achieve a minimum score on a standard IQ test (administered in person by a licensed psychologist). The law specifies a threshold of 130 points for non-disadvantaged students, but allows districts to select a lower "Plan B" threshold for FRL and ELL students, which the District sets at 116 points. Since IQ testing is costly ($1,000 or more for a test by a private psychologist), nearly all lower-income children are tested by District psychologists.

Once a student is found to meet the IQ threshold, the school's Exceptional Student Education (ESE) specialist meets with the student, parents and teachers to determine whether additional gifted criteria are met, including the "need for a special instructional program." The final determination weighs several factors, including test scores and behavioral indicators. The District's policy is intentionally flexible with respect to traditional criteria like leadership, creativity and motivation, so as not to eliminate gifted "underachievers" from the gifted program.

The District also promotes diversity in its gifted population through a "universal screening" program. Traditionally, students are referred for gifted evaluation through a process that depends on parents and teachers, leading to concerns about the under-representation of minorities and lower-income children (Ford, 1998). In 2005, the District began administering an in-class, non-verbal ability test to all 2nd graders; it then used cutoffs on this test (matching the IQ thresholds for gifted status) to generate automatic referrals for IQ testing. As documented in Card and Giuliano (2016a), this led to an immediate rise in the fraction of FRL and ELL children who received an IQ test (from 13% to 24%) and in the share identified as gifted by the end of 3rd grade (from 1.4% to 4.3%). Among all children eligible for Plan B in the cohorts covered in our schooling data, 26% had an IQ test and 3.6% were identified as gifted by the end of 5th grade.[19]

b. Gifted Services

Gifted students are eligible to receive gifted services through the end of high school. The starting point for these services is an EP, which is developed by an ESE specialist along with input from teachers and parents. State guidance instructs that the EP should identify: (i) the student's needs related to his or her area of giftedness (e.g., exceptional math ability) and (ii) the services that will be provided to ensure the student will progress appropriately. While gifted EP's must specify curriculum goals, they can also include social/emotional and "independent functioning" goals (e.g., related to homework completion). Indeed, state guidelines encourage staff to consider what is "the most important skill or behavior that the student needs in order to make progress commensurate with his/her abilities" (Florida Department of Education 2006).

Prior to 4th grade, gifted students typically receive a few hours per week of individualized instruction based on the learning goals in their EP. Starting in 2004 – and affecting 8 of the 10 cohorts in our analysis sample – the District mandated separate classrooms in 4th and 5th grades for all gifted students, with any extra seats filled by the school's highest-scoring students on the prior year's state-wide tests ("high achievers"). We refer to these as gifted/high achiever (GHA) classrooms. GHA classrooms follow the same curriculum and use the same textbooks as in regular classes, although gifted students (unlike the non-gifted high achievers in the same classrooms) continue to pursue individualized goals as assigned in their EP's.

Most of the District's middle schools also offer separate gifted/high achiever classes for language arts in grades 6-8. In addition, all middle schools offer a 3-year accelerated math program, known as "Great Explorations in Math" (GEM), which combines pre-algebra in 6th grade, algebra in 7th grade, and geometry in 8th grade. Students with a minimum score on the 5th-grade statewide math test are eligible to enter GEM; continuation in later years is based on course grades. Gifted students may receive priority for filling extra seats in a GEM class if there are not enough students scoring above the 5th-grade cutoff. In high school, gifted students often

[19] Of the 10 cohorts in our sample, 7 were exposed to universal screening; however, the rates of IQ testing varied across cohorts due to a scaling back of the program during the Great Recession (2008-2011), followed by its re-institution in 2012 using a different screening test.

take honors-level classes (such as calculus) or participate in specialized programs such as the International Baccalaureate. Many also take advanced placement (AP) courses.

Finally, gifted students have access to specialized teachers and counselors throughout their schooling careers. GHA classrooms at all grade levels are assigned teachers who have completed training in gifted education, including content related to disadvantaged populations and strategies to meet children' affective, social and emotional needs. Gifted students meet with their ESE specialist at least once every two years to review and update the goals in their EPs. In addition, at the transitions to middle and high school, students and parents meet with the ESE specialists of the sending and receiving schools. One goal of these meetings is to help students choose appropriate courses to match their abilities. The findings of Carlana et al. (2022) suggest that this guidance may be especially helpful for disadvantaged students who lack college-educated role models.

c. *Data Sources*

We use student-level data from the District's centralized record system for children who were enrolled in 5th grade in the 2003-2012 academic years. These records contain information on each student's gender, race/ethnicity, FRL/ELL status, and gifted status. They also include state-wide achievement test scores in reading and math for grades 3-8; disciplinary logs from grades 3-8; Stanford Achievement Test scores in 2nd grade (for 8 of our sample cohorts); scores from the gifted screening test that was adopted in 2005 and administered in 2nd grade (for 5 of our cohorts); and PSAT scores for all those who took the exam in high school (around 92% of our sample). Courses enrollments are available for grades 3-12, and course grades are available for middle and high school.

Information on college enrollment is reported to the District by the National Student Clearinghouse (NSC) and is available for all students who completed high school in the District. For a subset of grades and cohorts, we can also link student responses from various District-administered surveys. Finally, we link these records to IQ test scores for all students in our sample cohorts who were tested by the District or submitted a score on their own.

d. Analysis Sample and Descriptive Statistics

We derive our main analysis sample in three steps. First, we identify students who had a first IQ test administered by 5th grade, were ELL or FRL at the time of the test, scored 100-128 points, were enrolled in the District by 4th grade or earlier, and did not repeat 5th grade. Second, we require that the student stayed in the District for at least seven years after 5th grade, had non-missing test scores in grades 5-8, and had non-missing data on courses and grades in middle and high school.[20] This second step, which reduces the sample by around 25%, ensures that we can observe information on high school graduation and college entry. Finally, for our main analysis sample, we further limit attention to students with IQ's in the range of 106 to 124 points.

A potential concern with our sample is that students who achieve gifted status may be more (or less) likely to remain in the District through the end of high school, leading to selection biases. To address this concern, we use our "step 1" sample (and gender-specific sub-samples) to estimate RD models for the effect of passing the 116 IQ threshold on the probability of being in our "step 2" sample. The estimates are presented in Appendix Table A2. Reassuringly, these estimates are uniformly small and statistically insignificant.

Table 1 presents summary statistics for students in our main analysis sample, focusing on predetermined characteristics of students and their schools.[21] As a benchmark, column 1 reports statistics for all students who were in 5th grade in the District in 2003-2012. The district is racially and ethnically diverse, with roughly equal shares of White, Black and Hispanic students. About one-half were FRL-eligible and 8% were English language learners (ELL) – rates that are comparable to other large urban school districts.

We also summarize cognitive and non-cognitive skills in early grades. We measure cognitive skills in reading and math using (standardized) test scores on 2nd-grade Stanford Achievement tests (SAT's) and on 3rd-grade statewide tests. Since our data do not include information from elementary school report cards, we only have one measure of non-cognitive skills for 3rd-graders, based on student responses to a survey asking whether they "enjoy learning" at their school.[22] As show in column 1, most students report high levels of enjoyment, and nearly half rate their enjoyment in the highest category of a 5-point Likert scale.

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[20] Due to missing data in one year of our sample, high school course records are incomplete for 4 of our 10 cohorts. We include these cohorts in our analysis of high school GPA's by averaging over courses in available years; however, we omit these cohorts for our analysis of AP course-taking in high school. Our conclusions regarding high school GPA are robust to models fit to the restricted set of cohorts, and all our results are robust to specifications that include cohort fixed effects.

[21] Outcome variables are summarized in Appendix Table A3 and discussed later.

[22] In previous versions of this paper, we combined this measure with a count of disciplinary suspensions in third grade. The rate of suspensions is very low, however, especially among students with IQ's near 116 points. As a result, this variable contributed relatively little to the combination. For simplicity, and in response to concerns that these two measures capture very different non-cognitive attributes, we therefore focus solely on the school enjoyment question.

Column 2 describes our main analysis sample of Plan B students with a first-reported IQ test score in the 106-124-point range who were still in the District seven years after 5th grade. Consistent with their above-average IQ's, these students are relatively high-achieving, with mean test scores in 2nd and 3rd grade that are 0.5-0.6 standard deviations (σ's) above the District-wide average. They are also more likely to be minorities, have a high rate of FRL participation, and attended elementary schools with higher fractions of FRL participants and slightly lower standardized test scores than the sample in column 1. Interestingly, this high-IQ sample is only slightly more likely than the District-wide sample to have high non-cognitive skills. Columns 3 and 4 show characteristics of the analysis sample separately for boys and girls. There are relatively small differences between them, though girls have somewhat higher (by about 0.25 σ's) test scores in reading. Girls are also more likely to enjoy school, consistent with the gender gap in other indicators of non-cognitive skill. Columns 5 and 6 of the table show the characteristics of compliers for our RD analysis of gifted identification, which we discuss below.

III. Empirical Strategy

We adopt a fuzzy RD approach for analyzing the effect of gifted status on student outcomes, estimating a locally linear first-stage model for gifted status that has a jump at the threshold for Plan B gifted eligibility and parallel reduced-form models for outcomes like college enrollment. Under standard assumptions (e.g., Hahn, Todd and van der Klaauw, 2001), the ratio of the jump in the outcome at 116 points to the jump in the fraction of gifted students provides a causal estimate of the effect of gifted status on the compliers whose gifted status switches as their IQ score moves from just below to just above the Plan B threshold.

Specifically, our first-stage model takes the form:

$$Gifted_i = \pi \, 1[IQ_i \geq 116] + g(IQ_i) + u_i, \qquad (2)$$

where $Gifted_i$ is an indicator that student i was identified as gifted by 5th-grade and $g(IQ_i)$ is a piece-wise linear function of IQ that allows a slope change at $IQ = 116$:

$$g(IQ_i) = g_0 + g_1(IQ_i - 116) + g_2(IQ_i - 116) \times 1[IQ_i \geq 116].$$

We estimate this model using data for students with IQ scores in some (possibly asymmetric) bandwidths (BW) around the 116-point threshold: $116 - BW_L \leq IQ_i \leq 116 + BW_R$.

Likewise, we estimate reduced-form models for the jump in an outcome of interest, Y_i, at the 116-point threshold of the form:

$$Y_i = \delta\ 1[IQ_i \geq 116] + h(IQ_i) + u_i, \quad (3)$$

where $h(IQ_i)$ is a piece-wise linear function analogous to equation (2). Our IV estimate of the treatment effect of gifted status on the mean outcome of the compliers is $\hat{\beta} \equiv \hat{\delta}/\hat{\pi}$. We construct this using a two-stage least squares (2SLS) estimator for the second-stage model with gifted status on the right-hand side:

$$Y_i = \beta\ Gifted_i + f(IQ_i) + e_i, \quad (4)$$

using the indicator $1[IQ_i \geq 116]$ as an instrumental variable, and parameterizing $f(IQ_i)$ in the same way as $g(.)$ and $h(.)$. Our models have no covariates, but we show below that combinations of baseline characteristics that predict our outcomes are smooth at the 116-point threshold.

A standard approach to the choice of bandwidths BW_L and BW_R is the algorithm proposed by Calonico, Cattaneo and Titiunik (2014) (hereafter, CCT). Implicitly, this algorithm assumes that the running variable in the RD model is continuous. In our case, IQ is discrete with a relatively small number of values. We therefore proceed by considering results from a selection of bandwidths, including the BW's suggested by CCT. In our baseline approach, we consider symmetric bandwidths of 6, 8 and 10 points to the left and right of the threshold, treating 8 as our preferred option. For most of our outcomes, the estimates are robust to the choice of bandwidth. For our main outcome, we present a more extensive analysis, including visualizations of the range of estimates from a full two-dimensional grid of alternative bandwidths BW_L and BW_R.

IV. Main Results

a. Validity of the RD Design

In an ideal RD design, the running variable is exogenously determined (Lee 2008; McCrary 2008). In the case of IQ tests, however, psychologists have some discretion in assigning scores and can boost marginal students above the gifted threshold.[23] Figures 2a and 2b show the frequency distributions of IQ scores for boys and girls in our analysis sample. Even though we use only first-reported IQ scores, the histograms show evidence of manipulation, with a spike in the frequency at 116 points and deficits at 114 and 115 points.[24]

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[23] For example, in one section of the Wechsler Intelligence Scale for Children (4th edition), children are given two words – like "red and blue" – and are scored 0, 1, or 2 points based on their explanation for their similarity.

[24] In a sample that uses our preferred IQ bandwidth and includes all IQ scores near the threshold for Plan B eligibility, we conduct a McCrary (2008) test and reject the null hypothesis of continuity at the threshold (p-value < 0.001). Using a donut approach that excludes IQ scores of 114 to 116, we fail to reject the null hypothesis of continuity at the threshold (p-value = 0.878).

Given this situation, we use a parametric "donut" RD approach that excludes students with IQ scores of 114 to 116.[25] These specifications assume that the conditional means of the outcomes of interest are linear in IQ:

$$E[Y_i|IQ_i| = h_0 + h_1(IQ_i - 116), \qquad 116 - \mathrm{B}W_L \leq IQ_i \leq 116 \quad (5a)$$

$$= \delta + h_0 + (h_1 + h_2)(IQ_i - 116), \quad 116 \leq IQ_i \leq 116 + \mathrm{B}W_R \quad (5b)$$

allowing us to extrapolate from data outside the donut window back to the 116-point threshold and derive an estimate of δ. We make the same parametric assumption about our first-stage model to derive an estimate of π.

b. First-Stage Model and Compliers

Figures 3a and 3b show the relationships between IQ and the probability of being identified as gifted for boys and girls, respectively. We show the estimated probabilities for each IQ point (with the blue dots) along with pointwise 95% confidence intervals (indicated by the thin blue lines). The means for IQ scores inside the donut region are shown with open circles; we also shade this region. Finally, on each side of the donut, we show the estimated local linear fits for bandwidths of 6, 8, and 10 points, plotted in yellow, green, and red, respectively.

We note three features of the graphs. First, there are large jumps in the probability of gifted status at the Plan B threshold. To the left, the probabilities are low (around 8% for boys and 3% for girls, extrapolating to 116 points). To the right, the probabilities are much higher (around 58% for boys and 63% for girls). Second, gifted rates continue to rise with IQ to the right of the threshold. Third, the magnitude of the jump in the probability of gifted status is similar whether we use bandwidths of 6, 8, or 10 points for either boys or girls. Indeed, the estimates of our first stage model (presented in column 4 of Table 2) range from 47 to 52 ppts for boys and from 60 to 62 ppts for girls, with standard errors of around 5 ppts.

We use the method suggested by Abadie (2002) to estimate the characteristics of compliers whose gifted status is determined by whether their IQ's are marginally above or below the IQ threshold.[26] As shown in columns 5 and 6 of Table 1, compliers of both genders have relatively high 2nd and 3rd-grade scores: about 0.9σ's above the District-wide mean. This gap is about the same as the ~1σ gap between the Plan B IQ threshold and the population mean of IQ

[25] Another benefit of excluding IQ's just below the threshold is that it ensures our estimates are not confounded by psychological effects (e.g., disappointment) associated with just missing out on gifted status.
[26] Angrist, Hull and Walters (2023) describe how to apply this approach to estimate complier characteristics in a school lottery-based research design, and by extension, to an admissions RD, which they frame as a local lottery.

scores, suggesting that standardized test scores and IQ scores are generally aligned. Averaging test scores across subjects masks gender gaps by subject, however, with boys performing relatively well in math and girls in reading. There is also a relatively large gender gap among compliers in how much they report enjoying school.

For a subset of cohorts, we predict college enrollment based only on 2nd-grade measures of cognitive ability from a model fit to non-gifted, non-FRL girls (as in Figure 1) and estimate the complier means and quantiles of this index. The distribution of this index is very similar for boys and girls, with an overall mean of 0.78, and 10th and 90th percentiles of 0.72 and 0.81, respectively. These values are indicated with vertical lines on Figure 1 to illustrate that there are wide gender gaps in observed college entry rates, conditional on the index, in the range where most of our compliers are located.

c. The Effect of Gifted Identification on College Entry

We begin with the main outcome of our study: on-time completion of high school and entry to college in the following academic year (i.e., 7 years after completing 5th grade). Panel A of Figure 4 graphs mean rates of college entry by each level of IQ for boys and girls, using the same format as Figure 3. There is a clear jump in the college entry rate of boys at 116 points, although the precise magnitude depends on the bandwidth used to extrapolate from points outside the donut to the 116-point threshold, with a larger jump using a smaller bandwidth. In contrast, there is a relatively small jump (or possibly no jump) in the college entry rate for girls at the 116-threshold that is similar in size regardless of bandwidth.

As emphasized by Lee and Lemieux (2010), in a valid RD design, the predetermined characteristics of students with different IQ's should trend smoothly through the gifted threshold. We test this presumption in Panel B of Figure 4. Specifically, we use state-wide test scores and our non-cognitive index from 3rd grade, combined with student demographic variables, student cohort, and 5th-grade school characteristics, to predict the probability of college entry by gender.[27] We then plot the predicted probabilities at each IQ score, along with the associated confidence intervals. We also show estimated local linear models using bandwidths of 6, 8, and

[27] About 20% of gifted students are identified before 3rd grade, but there is no indication in our sample or in the previous literature that the services offered to gifted children in grades K-3 have any effect on test scores. Note that we get very similar results if we replace 3rd-grade test scores with 2nd-grade SAT scores in math and reading or the 2nd-grade Nonverbal Ability Index from the test used for gifted screening (see Appendix Figure A3). However, these measures are only available for about 70% of our sample and are missing entirely for some cohorts.

10 points. Reassuringly, the predicted probabilities are very smooth through the 116-point threshold, and the estimated discontinuities are small.[28] Interestingly, the figure for boys also shows evidence of deviations from the fitted lines for boys with IQ scores of 115 and 116, which is consistent with the type of selective manipulation that motivates our donut specification.

To probe the effects of bandwidth choice for our main outcome, we estimated a series of local linear specifications, using bandwidths of 3-14 points on left of the donut range (extending down to scores of 100) and 3-12 on the right (extending up to scores of 128).[29] We then constructed the full set of 120 estimates of the reduced-form jump in the probability of college entry. These are plotted in Figure 5 and shown, along with the corresponding 2SLS estimates, in Appendix Tables A5 and A6. The 2-dimensional surface of estimates for boys is relatively smooth and confirms that *smaller* bandwidths on either side of the threshold are associated with *larger* estimates of δ. Specifically, the estimated jump in college entry is around 30 ppt when both bandwidths are in the range of 3-4, but falls to around 7 ppt when the bandwidths are in the range of 12-14. Even at the widest bandwidths, however, the 2SLS estimates for boys imply marginally significant treatment effects of around 10 ppt. For girls, the 2-dimensional surface is not as smooth, but the range of estimates of δ is smaller.

We also conduct two additional exercises to further assess our choice of bandwidth. First, we applied the CCT algorithm to our data, specifying an initial range of IQ's of 100-128 (deleting IQ's of 114-116), a rectangular kernel, and the default regularization procedure. The symmetric MSE-optimal bandwidth selected by the CCT algorithm (with the default regularization procedure) is 3 for both boys and girls.[30] These choices lead to very large but imprecisely estimated reduced-form impacts of gifted eligibility for boys (32.0 ppt, s.e.=14.5 ppt), and small but imprecisely estimated impacts for girls (4.1 ppt, s.e.=14.1 ppt). Second, to evaluate the assumption of linear conditional expectations in equations (5a-5b) we constructed the root mean squared errors of models with different (symmetric) bandwidths (see Appendix

[28] Appendix Table A4 reports estimates of discontinuities at the threshold for all the individual pre-determined student characteristics that we use to predict the probability of college entry.

[29] We stop at 128 points because there is a small spike in the rate of gifted identification at 130 points (the gifted threshold for non-disadvantaged students) and a deficit at 129 points. We believe these patterns are attributable to slippage in the applicability of the Plan B threshold, e.g., arising from changes in family incomes or ELL status.

[30] CCT's default triangular kernel selects a slightly wider symmetric bandwidth (4.8) for girls, but not for boys, and selects asymmetric bandwidths that are also similar for boys (3.7 below and 2.7 above) but slightly wider for girls (3.7 below, 5.4 above). Applying the CCT algorithm *without* regularization produces bandwidths that are generally larger: for boys this leads to a bandwidth of 3 points above the threshold and 10 below; for girls the choices are 7 points above the threshold and 12 below.

Table A7). These are similar across bandwidths, as are the *p*-values of *F*-tests comparing linear models with given bandwidths to the unrestricted alternatives (with dummies for each IQ point). Given these results, we believe that choices of 6, 8, and 10 are broadly representative of the data.

Finally, returning to the visual evidence in Panel A of Figure 4 for boys, we offer two justifications for choosing 8 points as our preferred bandwidth. First, the reduced-form relationship is concave below the threshold, and this nonlinearity appears to bias the linear prediction for bandwidths > 8. Second, estimates using bandwidths < 8 lead to strongly negative slope estimates above the threshold that appear driven by an outlier at IQ=117.

Table 2 summarizes the first-stage and reduced-form models for our main outcome and presents the corresponding 2SLS estimates of the effect of gifted identification. Panel A presents the results for boys and Panel B for girls. We show estimates, standard errors (clustering by school in 5th grade), and sample sizes for symmetric bandwidth choices of 8, 6 and 10 points; in all cases, we exclude IQ's between 114 and 116.

We begin in columns 1-3 by testing for discontinuities in student characteristics. The dependent variable in column 1 is a student's average 2nd-grade SAT score, which is only available for about 70% of our sample.[31] There is no indication of a detectable discontinuity at the 116-point threshold. Column 2 presents models for 3rd-grade state-wide math and reading scores, which are available for a larger fraction of students in our sample: again, we find no evidence of any jump at the Plan B threshold. Finally, column 3 tests for jumps in the predicted probability of graduating on time and entering college, as visualized in Panel B of Figure 4. These also show no evidence of discontinuities.

Next, in column 4, we present the estimated first-stage effect of crossing the 116-point threshold on the probability of being identified as gifted. As noted in the discussion of Figure 3, the estimates are centered around 0.5 for boys and 0.6 for girls, are robust to bandwidth choice, and are highly significant (t-statistic ≥ 10), addressing any concern about a weak first stage.

Column 5 presents the reduced-form discontinuities in the probability of graduating on time and entering college the next year. For boys, the estimates range from 0.09 to 0.19 and are all statistically significant, while for girls they are uniformly small (0.02-0.04) and insignificant. We have also estimated models for the probability of graduating high school on time or at most one year late, and for completing high school on time and entering college within <u>two</u> years (see

[31] There is no detectable threshold crossing impact on the likelihood of having a 2nd-grade SAT score.

Appendix Table A8). The effects on high school graduation are consistently small, suggesting that the main impact of gifted identification is on college entry, rather than on completing high school, and that the effects on college entry within 1 or 2 years are very similar.

Finally, column 6 presents 2SLS estimates of the treatment on the treated effects of gifted identification on college entry (i.e., β in equation 4). For boys, the point estimates range from 18 ppts for a 10-point bandwidth to 41 ppts for a 6-point bandwidth, with our preferred 8-point bandwidth yielding an estimate of 28 ppts (with a 95% confidence interval of 7-48 ppts). For girls, the estimates are narrowly clustered between 3 and 7 ppts, though the 95% confidence interval for our preferred 8-point bandwidth runs from -14 ppts to 24 ppts, so we cannot rule out a zero effect or a relatively large effect of either sign.

Figure 6 illustrates how these impacts affect gender gaps by presenting the estimated mean potential outcomes for the complying boys (left side) and complying girls (right side) using an 8-point bandwidth. The estimated college entry rate for male compliers who narrowly miss the gifted threshold is 46%; the 28 ppt treatment effect of passing the threshold raises this to 74%, which equals the rate for female compliers who narrowly miss the threshold. In other words, being identified as gifted raises the college entry rate of marginally eligible boys to the *same* rate as girls, closing the gender gap that is present in the absence of gifted services.

d. Interpreting Gender Differences in the Effects of Gifted Education

The estimates in Table 2 suggest that gifted identification raises the college entry rate of boys much more than that of girls, though we cannot quite reject that the IV estimates are the same at conventional significance levels: the p-value is 0.077 for our preferred 8-point bandwidth and slightly higher for the 6- and 10-point bandwidths. Given the visual evidence in Figures 4 and 5, however, we believe there is fairly strong evidence of a gender difference.

More importantly, the next section shows that there is a parallel set of effects on a variety of outcomes in middle and high school that are usually interpreted as markers of non-cognitive skill. Specifically, for outcomes like grades and advanced course enrollment, we find that boys perform worse than girls at IQ scores just below 116, and that passing the gifted threshold leads to gains for boys that close or nearly close the gap with girls, but has no significant effects for girls. In contrast, for outcomes like standardized test scores that are usually interpreted as measures of cognitive skill, we find small and insignificant effects for both boys and girls.

Building on the simple model in Section 1, our interpretation of these patterns is that in the absence of gifted services, many disadvantaged boys with IQ's near the threshold have a non-cognitive skill deficit that limits their academic success. Most girls, on the other hand, have non-cognitive skills that are aligned with their cognitive skills. Assuming that non-cognitive and cognitive skills are strongly complementary, policies that boost non-cognitive skills but have no effect on cognitive skills will have positive effects for boys but little effect for girls.

This explanation suggests that if we were to compare girls and boys with similar levels of non-cognitive skills prior to receipt of gifted services, we would find that children with lower non-cognitive skills benefit from gifted services regardless of gender, while those with higher skills are less affected. To test this hypothesis, we stratify our sample using our measure of non-cognitive skills prior to receipt of gifted services (based on how much students report enjoying school). Specifically, we split the sample into two groups: those who report the strongest (5/5) response to liking school ("high enjoyment") and those who report lower responses ("lower enjoyment"). We then fit RD models for the effect of gifted status on college entry separately for students with high vs. low non-cognitive skills, and we estimate the mean potential outcomes of the male and female compliers in each group. Our findings are summarized in Figure 7. Graphs of the corresponding first-stage and reduced-form models are presented in Appendix Figure A4.

Among students with lower non-cognitive skills – the majority of whom are male – the untreated compliers have relatively low college entry rates, whereas the treated compliers rates are 75-80%. The implied effects of gifted services are large for both boys (61 ppt) and girls (27 ppt) but relatively imprecisely estimated. Among students with higher non-cognitive skills – the majority of whom are female – the untreated compliers have much higher college entry rates (65% for boys and 75% for girls) and the implied treatment effects of gifted services are small. There are still gender gaps in the treatment effect within each subgroup – which is not too surprising, given the limited power of our non-cognitive measure – but these gaps are much smaller than in the overall analysis sample, suggesting that differences by non-cognitive skill are the fundamental heterogeneity that drives the gender gap in the effect of gifted services.

e. Additional Subgroup Heterogeneity

Do the treatment effects of gifted services vary along dimensions other than gender and non-cognitive ability? We address this question in Appendix Figure A5, where we show 2SLS estimates of the effects of gifted identification from our preferred 8-point bandwidth models separately for different subgroups of boys and girls. We begin with race/ethnicity. For both boys and girls, the point estimates are slightly smaller for Black children, but not significantly so. Next, we separate students by socio-economic disadvantage and parental language. For girls, we see somewhat more positive estimates for those who do not receive free lunches and for those with non-English speaking parents, but we see no significant difference for boys. We also see no evidence of heterogeneity for either gender when we stratify by whether a student's average 3rd-grade test scores were above or below the median conditional on their IQ. Finally, stratifying students based on the share of FRL recipients or the average test scores at their schools again produces no evidence of heterogeneity for either boys or girls. In sum, we find no evidence of systematic heterogeneity by school characteristics or by student demographics other than gender, and no large differences within the gender groups other than the heterogeneity by non-cognitive skill noted in Figure 7.

V. Intermediate Outcomes

Next, we analyze a series of intermediate outcomes, starting in elementary school and proceeding through middle school and high school. We focus first on measures of advanced course selections and course grades – outcomes that are widely interpreted as (task-based) measures of non-cognitive skill when the level of cognitive skill is held constant (as it is in our RD models). We end the section by looking at standardized test scores, which we interpret as largely reflecting cognitive skills. To preview our results, we find that gifted identification leads to large positive treatment effects *only* for outcomes that reflect non-cognitive skill. Consistent with the model in Section I, most of these effects are positive and significant only for boys, whose outcomes in the absence of gifted services lag behind those of girls with similar cognitive ability.

a. Advanced Course Selections in Elementary, Middle and High School

In 2004, the District adopted a policy of assigning gifted children to separate classes in grades 4 and 5, comprised of gifted children entirely or a combination of gifted and high-achieving students (see Section II.b). In column 1 of Table 3, we find large 2SLS estimated impacts of gifted status on the likelihood of enrolling in a GHA classroom in 4th grade, with impacts of 70-82 ppt for boys and 45-55 ppt for girls. To help visualize these effects, Figure 8 shows GHA participation rates of the compliers in our RD analysis with and without gifted status. Among the non-gifted compliers who narrowly missed the IQ threshold, there is a large gender gap in GHA participation, with rates of 26% for boys but 43% for girls. For gifted compliers (i.e., those who narrowly pass the IQ threshold) GHA participation rates are comparable and even slightly higher for boys than girls (97% versus 92%).

Further investigation into the participation gap among children with IQ's just below the gifted threshold reveals that only about one third it is due to higher scores among girls on the 3rd-grade statewide tests that are used to rank non-gifted students for assignment to a 4th-grade GHA class. The majority of the gap is due to different rates of participation between non-gifted girls and boys with similar test scores.[32] We suspect that this "preference for girls" may be due in part to teacher and parent concerns about placing boys with better test scores but lower non-cognitive skills in GHA classes.

The next three columns in Table 3 present estimated effects of gifted status on participation in the District's accelerated math curriculum ("GEM") and on algebra completion in middle school. Eligibility for GEM in 6th grade is based on achieving a minimum 5th-grade math test score. As shown in Appendix Figure D1, Panel B, there is a large (≈ 40 ppt) discontinuity in participation at the GEM test-score threshold among students in our IQ-based RD sample, very similar in size for boys and girls. Nevertheless, GEM participation rates among students with scores under the threshold are relatively high, and not all students who score above the threshold actually enter GEM. In this setting, eligibility for gifted services could impact GEM in two ways: by increasing 5th-grade math scores; or by increasing participation conditional on scores, either to the left of the cutoff (where schools may prioritize gifted students when filling extra seats) or to the right of the cutoff (where gifted students may receive extra encouragement to participate in GEM).

Column 2 investigates the first pathway, presenting 2SLS estimates of the effect of gifted identification on having an above-threshold math test score. The point estimates for boys are in the range of 8-12 ppt, but far from statistical significance (i.e., t-statistics ≤ 1); the estimates for girls are more variable across bandwidths but uniformly insignificant. Column 3 looks at the total effect on GEM entry, with a visualization of the associated reduced form in Panel A of Figure 9. The graphs suggest that boys with IQ's just under 116 are less likely to enter GEM than

[32] Consistent with results in Card and Giuliano (2016b, Figure 4) there is significant non-compliance in GHA enrollment both above and below the rank-based admissions threshold.

comparable girls, and that passing the gifted eligibility threshold is associated with a jump in participation for boys that largely closes the gap. In contrast, there is no apparent effect for girls. Consistent with these impressions, the 2SLS estimates in column 3 show a relatively large (and statistically significant) effect of gifted status on GEM entry for boys (on the order of 25 ppt), but weakly negative effects for girls.[33] We conclude that most of the rise in GEM participation for gifted boys is coming from an increase in enrollment conditional on test scores, rather than from a rise in the share of boys with scores above the GEM threshold.[34]

Column 4 looks at a related measure of middle school math participation: the probability of completing Algebra 1 by the end of 8th grade.[35] The reduced forms are visualized in Panel B of Figure 9. Again, the graphs show that boys with IQ's < 116 under-perform relative to girls, and that passing the gifted threshold leads to gains for boys that close the gap, while having little effect on girls. The estimated effects on completing algebra are a little larger than the effects on GEM, highly significant, and robust to bandwidth choices. Again, the effects for girls are all slightly negative though not significant.

The large magnitude of the impacts of gifted status on boys' participation in advanced math in middle school, coupled with the zero effects for girls, suggests that this could be an important channel mediating the effect on college entry. Indeed, other research (e.g., Card and Payne, 2020) suggests that success in math is especially important for the college entry of boys since a disproportionate share choose to major in math-intensive fields like business, computer science, or engineering. Using a supplemental research design, we directly estimate the magnitude of the impact of GEM on the rise in college entry rates for boys in Section V.e below.

Finally, column 5 of Table 3 and Panel C of Figure 9 examine a high-school outcome closely linked to college entry: the number of completed AP courses. The graphs show the same contrast between boys and girls with IQ<116 that we see for course selections in middle school:

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[33] Note that the reduced form jumps in Figure 8 are multiplied by a factor of about 2 for boys and 1.67 for girls to derive the 2SLS estimates.

[34] We have also examined the gender gap in GEM enrollment among non-gifted compliers (students with IQ scores just below the gifted cutoff). We find that the higher participation of girls is mainly driven by a higher rate of participation in GEM conditional on 5th grade math scores, rather than by higher test scores of girls in this IQ range. This finding, along with the similar finding about the gender gap in GHA participation described above, suggest that among students with IQ's just below the gifted threshold, gender gaps in course enrollments are caused by gaps in non-cognitive skills that makes parents and teachers less likely to push boys into advanced classes.

[35] District middle schools offer an advanced math track in addition to GEM that provides access to Algebra-1 in 8th grade (rather than in 7th). Students who miss the GEM threshold (or score above the threshold but either do not enter or do not persist in GEM) may pursue the advanced track instead.

the number of AP classes is steadily rising in IQ for girls and reaches a level of about 4 courses for IQ's around 113-115 points, whereas for boys the relationship is much flatter and only reaches a level of about 2 courses. Crossing the 116-point threshold, however, pushes boys much closer to girls. Confirming the visual impression, the estimates in column 3 show a large effect of gifted status on boys' AP course-taking, with our preferred bandwidth yielding a +2.5 course effect (95% confidence interval = 0.7 to 4.2). In contrast, we see no effect for girls.

b. Course Grades and Disciplinary Actions

Table 4 reports results for additional non-cognitive outcomes in middle and high school, including course grades at both levels of schooling and rates of suspension in middle school. The estimates in column 1 show weakly positive point estimates for boys on middle school math grades but small negative estimates for girls. Given that gifted boys are more likely to take advanced courses, however, the fact that their grades are, if anything, slightly *higher* suggests some gain in achievement. In column 2, the dependent variable is an indicator for never having received a suspension (internal or external) in middle school. Here, we again see weakly positive estimated effects for boys and zero effect for girls. Though the estimates are all insignificant, plots of the reduced-form relationships, presented in Panel A of Figure 10, show patterns similar to those seen for the course-taking outcomes in Figure 9. There is a large gender gap at IQ's below the gifted threshold, with a "no-suspension" rate that is 15-20 ppt lower for boys than for girls. Crossing the threshold appears to narrow this gap.

The remaining columns in Table 4 examine high school grade point averages (on a 4-point scale) in math courses (column 3), English language arts courses (column 4), and all courses taken in high school (column 5). The reduced forms associated with columns 3 and 5 are plotted in Panels B and C of Figure 10. Both figures show that in the absence of gifted services, boys have much lower grades than same-IQ girls, with gaps of around 0.6 in math and 0.35 in overall high-school GPA. In the case of math grades, gifted status has marginally significant effects on boys that range from 0.37 to 0.50 – enough to reduce, but not quite close, the gap with girls. Interestingly, there is no corresponding effect for boys on language arts grades, and the net effect on overall GPA is small. And, in no case do we see significant effects for girls; the estimates are either close to zero or weakly negative.

c. Quality of Classroom Peers

Overall, we interpret the results in Table 3 and 4 as supporting the hypothesis that being identified as gifted increases boys' engagement in school, leading them to take (or be accepted into) more advanced math courses in middle school and earn higher math grades in high school. As noted, however, a concern for interpreting the effect of gifted status on course grades is that gifted students may take harder courses. In fact, there is evidence from responses to student questionnaires administered by the District that gifted students are guided toward more challenging classes. Column 1 of Table 5 presents 2SLS estimates of the effect of gifted status on responses by 6th graders to a question asking if they agreed with the statement: "This year, school staff helped me to select high level courses that challenge my abilities." (Graphs of the corresponding reduced-form relationships are presented in Appendix Figure A6).[36] The estimates suggest relatively large effects (around 0.7 σ's for boys and 1.3 σ's for girls).

To quantify the impacts of gifted status on the levels of classes actually taken by students, we use information on the early-grade test scores of classmates.[37] This approach sidesteps difficulties in distinguishing the level of a class from its title or number and provides a metric that can be compared across subject domains. Columns 2-7 of Table 5 summarize 2SLS estimates of the effect of gifted status on classmate test scores in middle and high school. Associated graphs of the reduced-form relationships are shown in Appendix Figure A7.

Inspection of the reduced-form graphs reveals patterns closely paralleling our findings for on-time college entry. For girls, there is a systematic positive relationship between IQ and peer quality throughout the full range of IQ's, with no evidence of a discontinuity around 116 points. In contrast, for boys with IQ's under the 116-point threshold, the relationship between IQ and peers is relatively flat, and at the gifted threshold we see jumps in peer quality that nearly close the gaps with similar-IQ girls.

Consistent with the reduced-form patterns, the 2SLS estimates for boys in Table 5 show positive effects of gifted identification on peer quality in all subjects and at all levels of schooling. The impacts are statistically significant for our preferred 8-point bandwidth (in the

[36] The responses are collected on a 5-point Likert scale; the standard deviation of responses is 1.24. The student questionnaire was only collected in the 2008-2011 academic years for 5th-grade cohorts, so responses are missing for over one-half of our main sample. We find no statistically significant effect of gifted status on the probability of having a response (see Panel B of Appendix Figure A6).
[37] Specifically, we use state standardized test scores in reading and math, averaged over grades 3-5.

first row of Panel A) and centered around 0.3-0.4 standard deviation units. To the extent that teachers assign grades based on relative ranks, even the null effects on course grades in language arts for gifted boys noted in Table 4 might imply some improvement in effort and engagement.

In contrast to the effects of gifted status on peer quality for boys, for girls there is a significant effect only on middle school language arts classes. The differences between boys and girls are visualized in Figure 11, where we show the mean potential outcomes of peer quality for compliers in middle and high school.[38] At both levels, we find that untreated female compliers are in classes with higher scoring peers than untreated male compliers, and that the treatment of gifted status largely closes the gender gap.

One possible explanation for the negligible effect on peer quality for girls is that they are already in the highest-level classes in their school. To test this, we estimated variants of the reduced-form relationships shown in Appendix Figure A7 using peer quality deviated from the mean for all students in the same school. These graphs (which are not reported) show very similar positive slopes between IQ and relative peer quality, even for girls with IQ's above the gifted threshold, suggesting that topping-out is not the explanation. Instead, we suspect that girls' class selections – like their other outcomes – are aligned with their cognitive skills, which as we show next were unaffected by gifted services.

The positive impact of gifted services on the peer quality experienced by gifted boys suggests that peer quality could one of the mediators that contributes to the increase in their college entry rates. Higher scoring peers could lead to a change in effort norms, or to a change in aspirations for post-secondary education. Unfortunately, it is very difficult to pin down the magnitude of such potential peer effects in our setting. We note, however, that two recent studies of the impact of selective high schools suggest that such peer effects are likely small.[39]

d. Cognitive Skills in Middle and High School

We conclude this section by examining whether gifted status affects *cognitive* skills as measured by test scores in middle and high school. Starting with middle school, Panels A and B

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[38] See Appendix B, where we present bar charts similar to Figure 6 that compare potential outcomes of complying boys and girls, with and without gifted status, for all intermediate outcomes. The corresponding estimates for non-gifted compliers are reported in Appendix Table A3.

[39] Abdulkadiroglu et al. (2014) and Dobbie and Fryer (2014) both use regression discontinuity designs to study the effect of entry into selective high schools on college-related outcomes. Both studies find no impacts – see also Angrist (2014). In an earlier review of the peer literature, however, Sacerdote (2011) argues that peer effects in education tend to be positive.

of Figure 12 and columns 1-2 of Table 6 show results for standardized test scores in math and reading, averaged over grades 6-8. The graphs for both subjects show a strong positive relationship between IQ and test scores for both boys and girls, with roughly similar slopes for the two genders, and no evidence of a flatter relation for boys with IQ<116 (unlike the patterns seen in college enrollment and several of the non-cognitive outcomes).[40] Also, distinct from most of our "non-cognitive" outcomes for boys, Panels A and B show no evidence of discontinuity at the gifted threshold for either boys or girls – an impression that is confirmed by the small and insignificant treatment effect estimates in columns 1 and 2 of Table 6. Interestingly, while the reduced-form figures for math scores are similar for boys and girls, for reading, the entire test score-IQ relationship is lower for boys.

We reach similar conclusions about the effect of gifted status on cognitive skills when we measure these skills in high school. Here, we use the student's national percentile score on the PSAT exam, which is taken by most students in eleventh grade.[41] Figure 12 shows the reduced-form relationships between IQ and PSAT percentiles on the math (Panel C) and verbal (Panel D) subtests, while columns 3 and 4 of Table 5 present 2SLS estimates of the effect of gifted status. Looking first at the figures, we again see evidence that boys "under-perform" relative to girls on the verbal portion of the PSAT but not on the math portion. And again, there is no evidence of a discontinuity at the gifted threshold in boys' or girls' scores on either subject. These results are confirmed by the estimates in Table 5, which show no significant effect of gifted status on PSAT scores in either math or reading.

In sum, our analysis of intermediate outcomes suggests that gifted status pushes boys into more challenging courses and catches them up to girls with similar IQ's. The gendered effects on course selection are particularly striking in math, where boys just below the gifted threshold are less likely than their female counterparts to take advanced coursework, despite having similar test scores in math. Notably, gifted status also helps to narrow a wide gender gap in math grades

[40] Converting IQ to standard deviation units, the slopes are around 0.7 – i.e., a 1σ rise in IQ's leads to about +0.7σ rise in standardized tests.

[41] The PSAT, short for Preliminary SAT, is administered during school as an opportunity for students to practice for the College Board's SAT (which is distinct from the Stanford Achievement test, also referred to above as the SAT); it also serves as the National Merit Scholarship Qualifying Test. We use the maximum score for students who take the PSAT more than once. We use PSAT instead of SAT scores because participation rates are much higher (around 92% vs. 70% for our cohorts) and because the SAT scoring system was revised during our sample period (whereas PSAT scores are reported to the District as national percentiles). Results for the SAT scores (Appendix Table A9) are very similar but slightly noisier. Estimates for the effect of gifted status on the likelihood of taking the SAT are also uniformly close to zero.

despite having no detectable impact on test scores. Together, these results suggest that for boys near the 116 IQ threshold, gifted services "work" by narrowing the gap between their cognitive and non-cognitive skills, especially in the math domain.

VI. A Closer Look at Two Potential Mediators

In this section, we take a closer look at two potential mediators of the effect of gifted identification on college entry: participation in GHA classrooms in grades 4 and 5, and participation in GEM in middle school. The analysis of GHA classes is complicated by the fact that under the District's policies, all gifted students are placed in these classes. An analysis of GEM is more straightforward because entry to the program is based on 5th-grade math test scores and was not guaranteed for gifted students.

a. Gifted/High-Achiever Classrooms

Though nearly all gifted students are placed in GHA classes, non-gifted high achievers are also placed in these classrooms, leading to a fuzzy discontinuity in GHA participation at the gifted threshold. As seen in Figure 8, the size of the discontinuity is larger for boys than girls, largely because non-gifted girls with IQ's just below the 116-point threshold were more likely to be placed in a GHA class. This raises the question of whether some of the larger effect of gifted identification on boys' college entry can be attributed to their larger jump in GHA enrollment.

To address this question, we exploit variation across elementary schools in the numbers of gifted children per grade to stratify our sample into two groups: schools with relatively few GHA seats available for non-gifted high achievers, and those where more seats are available.[42] As we show in Appendix Figure C1, schools in the first group have less room for gender gaps in GHA participation for children without gifted status. As a result, the effect of gifted status on GHA placement is more similar between boys and girls at these schools (and if anything, is slightly larger for girls). However, there is no evidence of a treatment effect on college entry for girls in this sample, while the estimated effect for boys is even larger than in our overall sample. In the second group of schools, the treatment effect of gifted status on GHA participation is much smaller for girls, and the effects on college entry are more similar between boys and

[42] We also explored using variation in access to GHA classrooms based on cohort and age at gifted identification. However, the numbers of students who lacked access to a GHA classroom because the mandate was not in effect for their cohort or because they entered the gifted program too late are too small for meaningful sub-group analysis.

girls.[43] In light of these patterns, we find it unlikely that the small effect of gifted services on college entry for girls is due to their smaller average jump in GHA participation. Instead, we suspect that their relative abundance of non-cognitive skills explains the relatively small effects of gifted status for girls on *both* college entry and GHA participation.

A remaining question is whether GHA participation has gender-specific impacts on subsequent outcomes in middle and high school. Specifically, is GHA participation for boys the causal factor that leads to the non-cognitive gains found in our main analysis of the effects of gifted education? To study this question, we rely on an alternative sample that consists of *non-gifted* students whose 3rd-grade tests scores are near the top of their school/grade cohort. Our research design follows Card and Giuliano (2016b) and relies on the fact that open seats in a GHA classroom are allocated to non-gifted high-achievers based on relative ranks on an index of 3rd-grade scores. For comparability with our gifted analysis sample, we focus on boys and girls in this high-achiever sample who were FRL participants or English Language Learners. Unfortunately, the subset of non-gifted students whose GHA status in 4th and 5th grades is available in our data has very little overlap with the subset of students for whom we can observe high school outcomes and college entry. Thus, we limit our analysis to the impacts of GHA participation on middle school outcomes. The results are summarized in Appendix Table C2.

In brief, we find significant first-stage effects on GHA enrollment from having a 3rd-grade test score index above the presumed cutoff for a student's school and cohort. Reassuringly, we find no effect of test score rank on 3rd-grade test scores or on our measure of non-cognitive skill in 3rd grade (used in Figure 7), suggesting that the conditions for a valid RD are satisfied. Fitting 2SLS models for the various middle school outcomes, we find relatively large and marginally significant effects for boys on GEM enrollment, completion of algebra in middle school, the "no suspension" indicator, and math test scores. For girls, we generally find smaller and insignificant effects; however, the effect on combined test scores in reading and math (col. 8) is marginally significant and only slightly smaller than that for boys.

Whether these results translate to the students of primary interest in this paper – boys with IQ scores around the gifted threshold – is hard to know. Most of the compliers for gifted status are <u>not</u> high achievers (as evidenced by the low rate of GHA participation for non-gifted

[43] Details on the construction of the two samples are in the notes to Appendix Figure C1. The corresponding estimates are presented in Appendix Table C1.

boys, noted in Figure 8). Moreover, as shown in Appendix Table A1, the two groups differ on several other dimensions. Perhaps most importantly, the estimates in Appendix Table C2 suggest (consistent with the findings of Card and Giuliano 2016b) that for non-gifted high achievers of both genders, GHA entry leads to sizeable gains in standardized test scores. In contrast, we find no impact of the entire package of gifted services (including GHA classrooms) on the test scores of boys or girls with IQ's around the gifted threshold. Thus, while it is possible that the effects of GHA classes on the *non-cognitive* skills of compliers at the gifted threshold are similar to the effects that we can measure for high achievers, the differential impacts on *cognitive* skills between these two groups suggests that we should be cautious about extrapolating.[44]

b. GEM

Gifted status is associated with a rise in GEM participation for boys, along with subsequent gains in various math-related outcomes in high school. The fact that GEM precedes the changes in high school course-taking and achievement raises the question of whether GEM is a significant mediator of the rise in college entry for gifted boys. To answer this, we estimate the causal effects of GEM entry directly, using the 5th-grade math test score cutoff for GEM eligibility. Using the subset of students in our main analysis sample whose 5th-grade math test scores lie within a narrow bandwidth of the GEM threshold, we conduct an RD analysis of the effects of entering GEM in 6th grade on the probability of graduating high school on time and entering college (i.e., our main outcome). If GEM participation is in fact the key driver of the gains in college entry for gifted boys, then we expect these RD models to show large causal effects – large enough to account for all or most of the effect of gifted status on college entry.

The results are presented in Appendix Table D1, which closely parallels Table 2. To summarize, we find that pre-determined student characteristics trend smoothly through the GEM cutoff, but GEM participation rises sharply at the threshold, with jumps for both boys and girls in the range of 35 to 42 ppt that are robust to the choice of bandwidth.[45] We find a positive and statistically significant reduced-form effect of passing the GEM threshold on college entry for boys, on the order of 11 ppts, and a 2SLS estimate of the effect of GEM of 28 ppts that is

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[44] One possible reason for the differential effects on 4th and 5th-grade test scores – suggested to us in interviews with District teachers and administrators – is that gifted children are typically assigned enrichment activities while their non-gifted GHA classmates practice test-taking skills in the weeks leading up to standardized testing.

[45] Appendix Figure D1 illustrates the reduced-form relationship between the running variable and GEM participation (Panel B) and the analogous relationships for gifted status (Panel C).

marginally significant (*t*–statistic≈2). By comparison, the reduced-form and 2SLS estimates for girls are all relatively small in magnitude and insignificantly different from zero.[46]

Taken at face value, the estimated 28 ppt effect of GEM on college entry for boys, coupled with the fact that gifted status leads to 26 ppt increase in GEM participation of boys (Table 3) implies that GEM can account for only about <u>one-quarter</u> of the overall 28 ppt effect of gifted status on college entry of boys. Moreover, as shown in Appendix Figure D4, there is no indication that GEM participation has any effect on high school math grades or AP courses of boys. Thus, we conclude that GEM participation is probably <u>one</u> of the channels contributing to the effect of gifted status on boys' college entry rates, but that gifted identification has other effects, including impacts on high school course selection, that are not mediated by GEM.[47]

VII. Interpretation and Conclusions

Students who are identified as gifted in the District receive a package of services, including some individualized instruction in grades 1-3; assignment to separate gifted/high achiever classrooms in 4th and 5th grades; and biannual meetings with gifted specialists throughout their school careers. Despite the modest nature of these services, they appear to have relatively large effects on the college entry rate of boys, and on their middle and high school course selections and grades. At the same time, there is little evidence of corresponding effects for girls, or on standardized test scores of either gender.

Table 7 summarizes our main findings, grouping outcomes by whether they are usually interpreted as markers of non-cognitive skill (Panel A), cognitive skill (Panel B) or longer-run achievement (Panel C), and sorting within each group by the level of schooling. Column 1 of the table shows the mean potential outcomes for non-gifted female compliers. Column 2 shows the gender gap in mean outcomes of the non-gifted compliers. Column 3 shows the estimated treatment effect of gifted services on the outcome for boys, and column 4 shows the gap between the treatment effects for boys and girls.

As we have seen in many of the previous figures, the results in columns 1 and 2 show that boys with IQ scores just under 116 points appear to have substantially lower non-cognitive

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[46] Appendix Figure D2 shows the reduced-form relationships for boys and girls using the three selected bandwidths, and Appendix Figure D3 plots reduced-form estimates for the full range of bandwidths between 5 and 30.

[47] A caveat – suggesting that some caution is warranted when extrapolating from the RD results in Appendix D to the gifted population – is that the compliers with the 5th-grade math score cutoff for GEM differ from the gifted compliers who are pushed into GEM when their IQ score exceeds 116. As shown in Appendix Table D2, IQ-based compliers have lower average test scores and lower non-cog skills than compliers based on 5th-grade math scores.

skills than similar-IQ girls, with gender gaps of around 30-50% of the girls' mean for many outcomes in Panel A (e.g., a 47% gap in GEM enrollment and a 46% gap in the number of AP courses completed). The gender gaps in measures of cognitive skills (Panel B) are generally smaller, particularly in the math domain (e.g., only a 0.04σ gap in grade 6-8 math scores, and essentially a zero gap in PSAT math scores). Finally, the gender gap in the college entry rate of the non-gifted compliers is also large (0.28 for boys versus 0.74 for girls, equivalent to 38% of the girls' mean).

We see positive treatment effects of gifted services on nearly all the non-cognitive outcomes for boys, coupled in most cases with small effects on girls, so the relative treatment effect on boys versus girls (column 4) is often about as large as the boys' effect (in column 3).[48] Interestingly, many of the relative treatment effects on boys are also large enough to fully offset the gender gap in means of the untreated compliers (i.e., the entry in column 4 is about the same size as the entry in column 2), meaning that gifted services appear to close or nearly close the gender gap in non-cognitive skills. In contrast, none of the treatment effects on cognitive outcomes of boys (or girls) is even marginally significant.

How can we interpret this combination of effects? Previous research (e.g., Heckman et al., 2006) has argued that cognitive and non-cognitive skills are strong complements in the production of educational attainment. Other work (e.g., Jacob, 2002; Cornwell et al., 2013) has asserted that boys have lower non-cognitive skills than girls with similar cognitive skills. Putting these two strands of work together in a simple framework, we showed in Section I that an intervention that raised non-cognitive skills, with no effect on cognitive skills, would be expected to improve the educational outcomes of boys, while having small impacts on most girls. Differentiating between skills in the math and non-math domains provides an even richer set of implications, since boys who are marginally qualified for gifted identification tend to have relatively high cognitive skills in math. In that case we might expect an intervention that raised non-cognitive skills to yield particularly large gains in math-related course selections and grades for boys in middle and high school.

[48] To address concerns about multiple hypothesis testing, we report a parallel set of treatment effect estimates in Appendix Table A10, along with the conventional p-values and adjusted "*q*-values" that control for the false discovery rate (FDR) using the two-step procedure from Benjamini, Krieger, and Yekutieli (2006). All of the estimates that are at least marginally significant using conventional p-values remains so, and the effect on college enrollment remains significant with an adjusted q-value of 0.022.

We believe this very simple framework provides a successful interpretation for our main results. The gifted education literature has long emphasized the importance of targeted gifted services to help children with high cognitive abilities achieve their full potential. In particular, this literature has noted that when gifted students are not appropriately challenged or motivated to exert effort in school, they may fail to develop critical skills like self-regulation (Reis and McCoach 2000; Siegle and McCoach 2005). A model with strong complementarity between cognitive and non-cognitive skills provides a plausible framework for interpreting the impacts of an intervention that shifts non-cognitive factors linked to underachievement.

We acknowledge that some researchers (e.g., Fortin, Oreopoulos, and Phipps, 2015; Lundberg, 2020) have argued that the gender gap in schooling outcomes arises not from a non-cognitive skills deficit but because boys have gender-stereotypical aspirations that lead to negative attitudes toward school. This hypothesis has many of the same implications as one based on non-cognitive skills and is not incompatible with our findings; indeed, the treatment effects we find may operate both by shaping boys' long-term goals and by boosting their capacity to persevere toward those goals. Further research could benefit from settings with richer measures of non-cognitive skills that could be compared across age groups to verify that these skills are raised by gifted services. It is also possible that some of the effects we measure could be mediated through changes in how educators treat children when they are identified as gifted – potentially compensating for deficits in either non-cognitive skills or aspirations through more supportive interactions or providing greater encouragement. To the extent that this is true, we might expect to see smaller treatment effects on college completion and other longer-run outcomes. This is another area that would benefit from further research.

Overall, our findings add to the growing evidence that long-run schooling outcomes depend on more than just cognitive ability; that the other determinants of school success (non-cognitive skill, aspirations, engagement) are differentially distributed between boys and girls; and that "small" interventions can substantially affect schooling outcomes via these other channels. Importantly, even relatively large impacts on these alternative channels may not be detected by standardized tests. In our case, gifted status has no significant effect on standardized tests measured in grades 5-8, even though it causes large changes in boys' middle school math curriculum and grades, and in their classroom peers. Moreover, there is no effect on PSAT scores, despite boosts in high school math GPA's, high school classroom peer quality, and the number of AP classes.

With respect to the gifted education literature, our findings provide the first rigorous evidence from a U.S. setting that gifted programming can have long term effects on disadvantaged students. Previous evaluations (e.g., Bui et al, 2014; Card and Giuliano, 2014) have focused on standardized test scores and found no impact. Our findings, and related findings by Cohodes (2020), suggest that it is important to look beyond standardized test scores to understand the value of advanced academic programming. Since disadvantaged boys (even those with high cognitive abilities) have low college entry rates, this is a natural metric in our setting. For non-disadvantaged student populations, however, it may be necessary to look beyond college entry and focus on outcomes like advanced degree attainment, field of study, or even earnings (Booij et al., 2016; Lavy and Goldstein, 2022).

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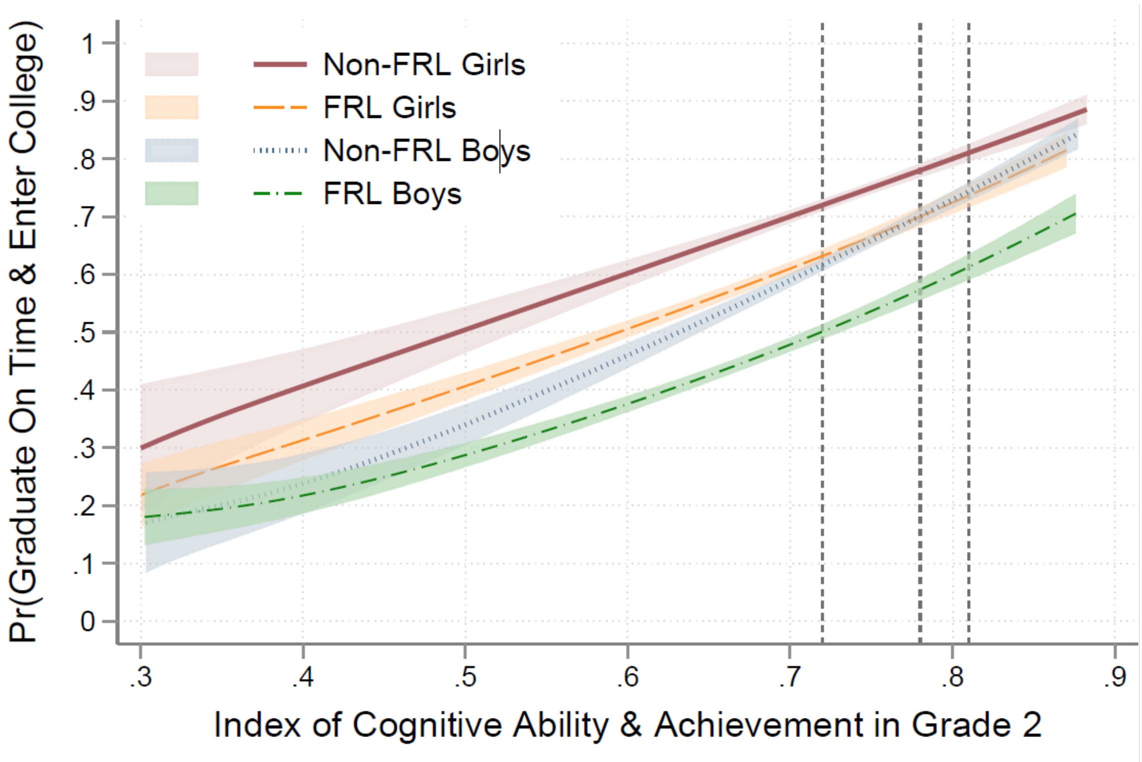
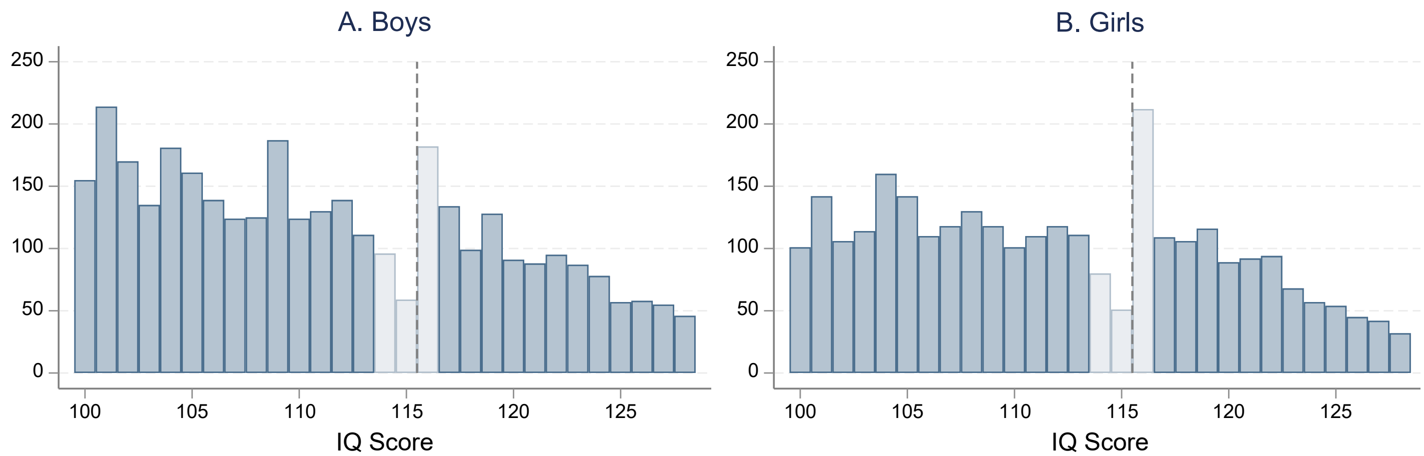
Figure 1. Gaps in College Entry by Cognitive Ability & Achievement in Grade 2



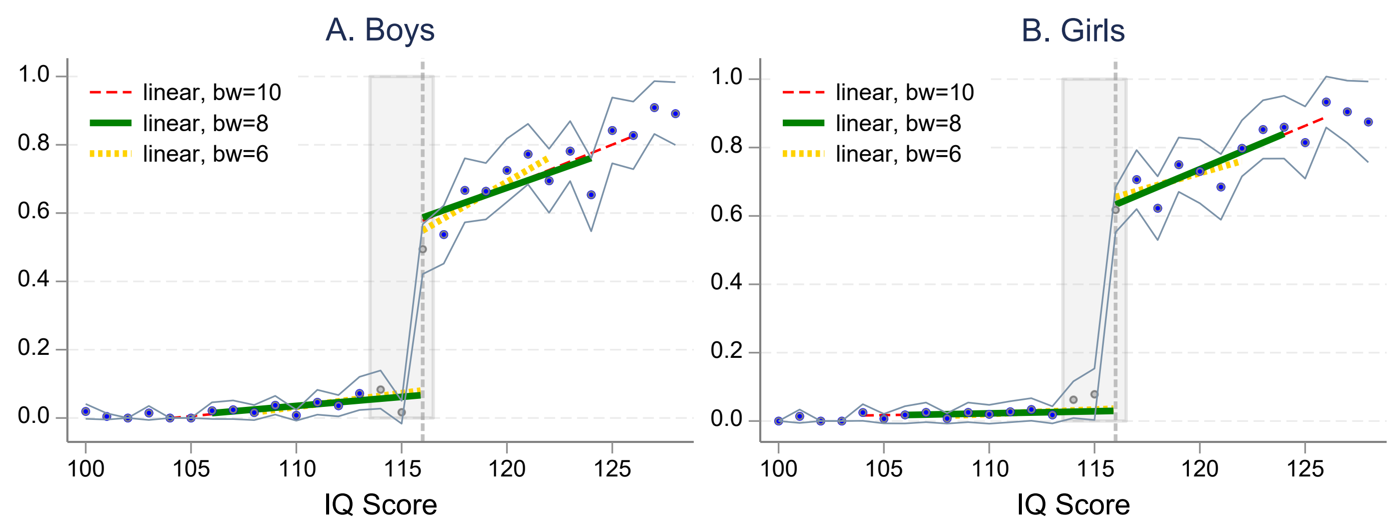
Note: This figure plots estimated means and 95% confidence intervals of an indicator for on-time high school graduation and college entry against an index of cognitive ability and academic achievement in grade 2. The index is constructed as the predicted probability of graduating on time and entering college from a model fit to non-gifted, non-FRL girls; hence, the means for Non-FRL Girls fall along the 45% line in by construction. Ability and achievement are measured using scores from three tests administered to all second graders in the District in the spring of 2005, 2006, and 2007: the Naglieri Nonverbal Ability Test (NNAT) and the Stanford Achievement Tests (SAT) in math and reading. The sample includes all students in these three cohorts who were not identified as gifted by the end of fifth grade and who could be followed in our data for at least 10 years after they were enrolled in grade 2. The means and confidence intervals are smoothed using a local linear bi-weight kernel regression (bandwidth = 0.45). The dashed vertical lines indicate the mean (0.78) and 10th and 90th percentiles (0.72, 0.81) of the index among compliers in the IQ-based RD analysis.

Figure 2. Histograms of Running Variable (First IQ Score), by Student Gender



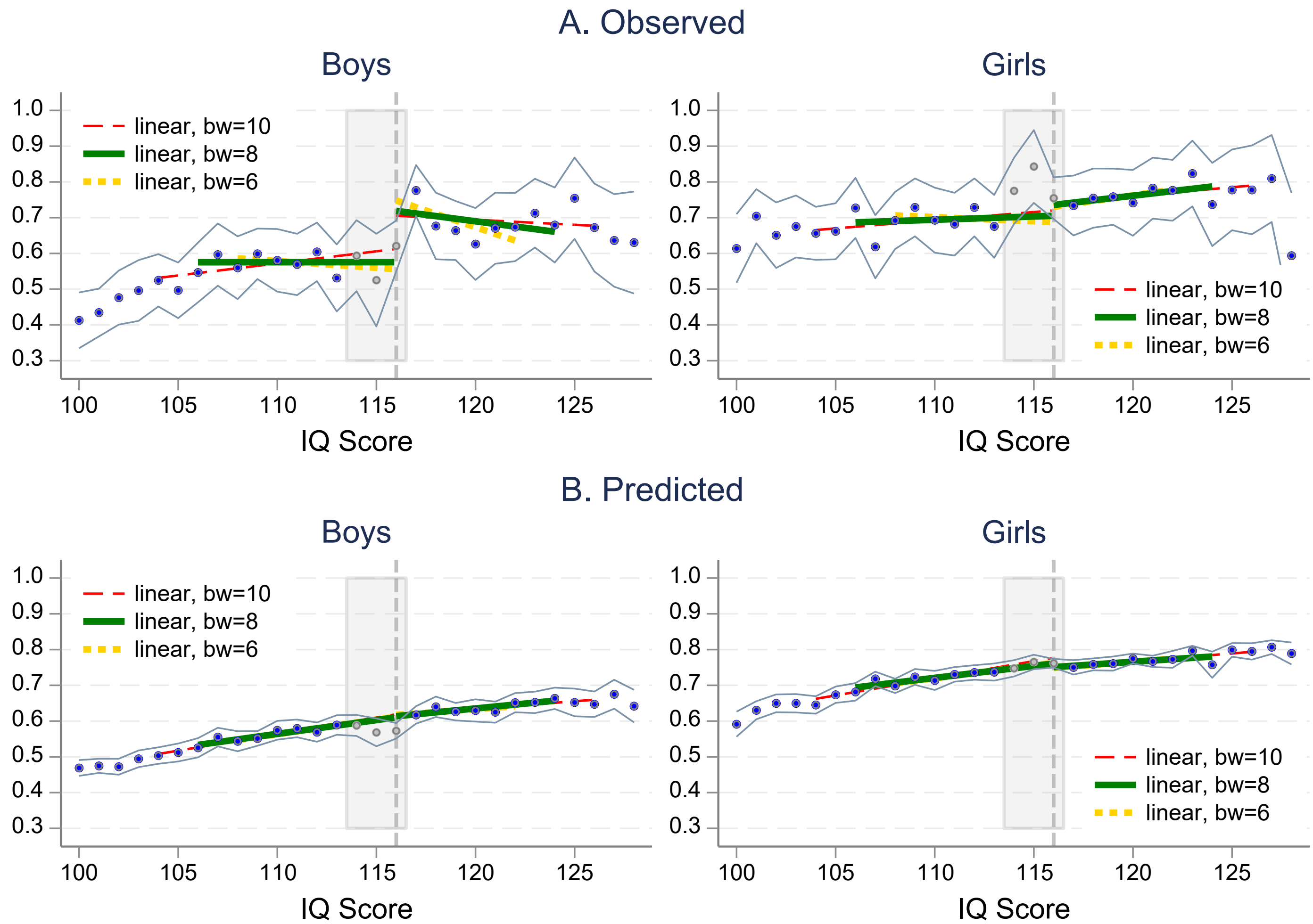
Note: This figure shows frequency distributions of the student IQ scores used to estimate our RD models separately for boys (Panel A) and girls (Panel B). The sample includes all students in the District who entered grade 5 in 2003-2012; who had an IQ score by the end of grade 5; who were eligible for a free or reduced-price lunch (FRL) and/or were enrolled in the English-language learner (ELL) program at the time of their IQ test; and whose first recorded IQ score is 100-128. For students with multiple IQ scores, we use the score from the earliest evaluation. The dashed vertical lines indicate the gifted eligibility threshold of IQ ≥ 116 for FRL/ELL students. The range displayed in a lighter shade (114–116) is the "donut" hole that is excluded from the estimation sample.

Figure 3. First-Stage Relationship for Gifted Status



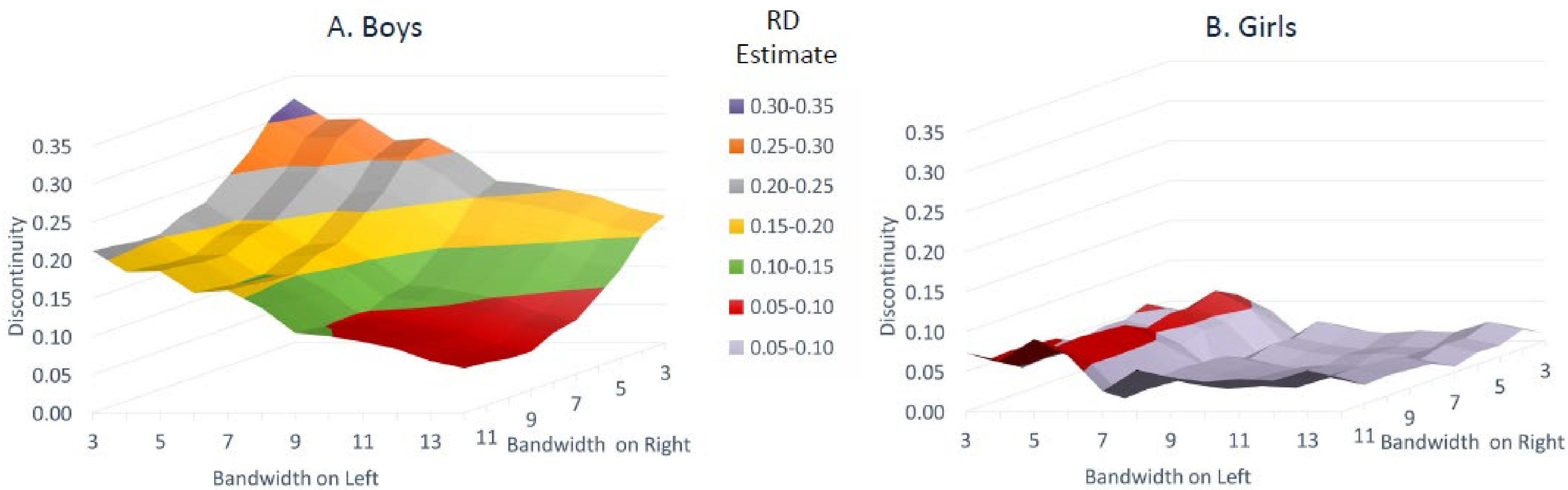
Note: This figure plots sample means (blue dots) of an indicator for gifted status (as of the end of 5th grade) at each value of IQ, for boys (Panel A) and girls (Panel B). It also shows 95% confidence intervals for the IQ-specific means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles.

Figure 4: Reduced-Form Relationships for On-Time Graduation and College Entry



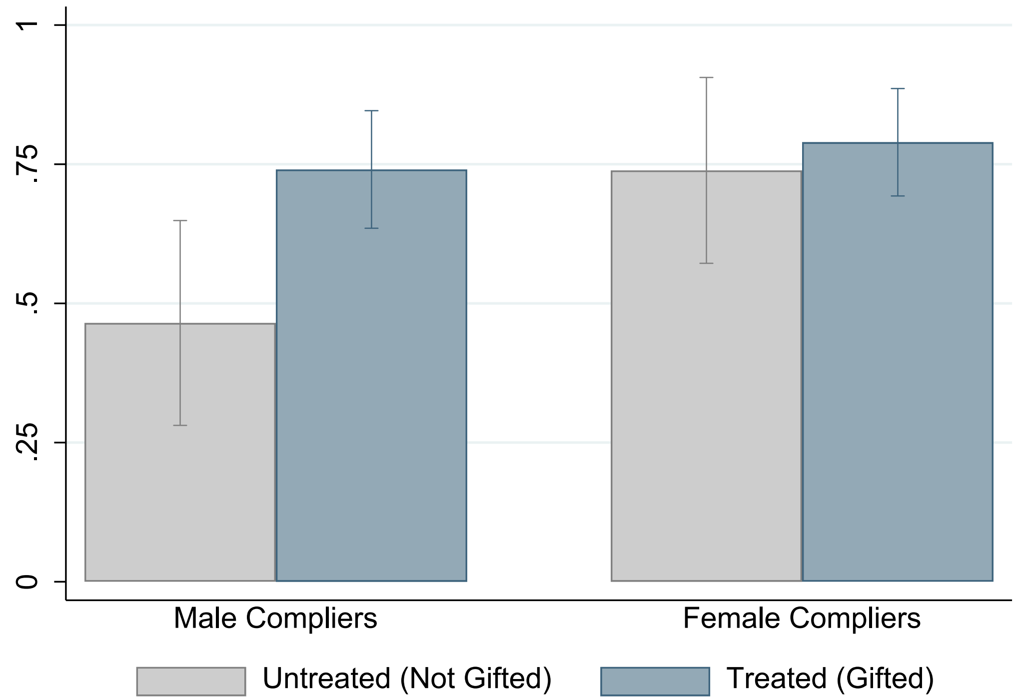
Note: This figure plots sample means (blue dots) of the dependent variable at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles. In Panel A, the dependent variable is an indicator for graduating high school on time and entering college within one year. In Panel B, the dependent variable is the predicted probability of on-time graduation and college entry from models fit separately to boys and girls with IQ scores in the range 100–115, using 3rd-grade test scores, survey responses, disciplinary records, student demographics, and school and neighborhood characteristics.

Figure 5: Estimated Discontinuities for On-Time Graduation and College Entry with Varying Bandwidths on Left and Right



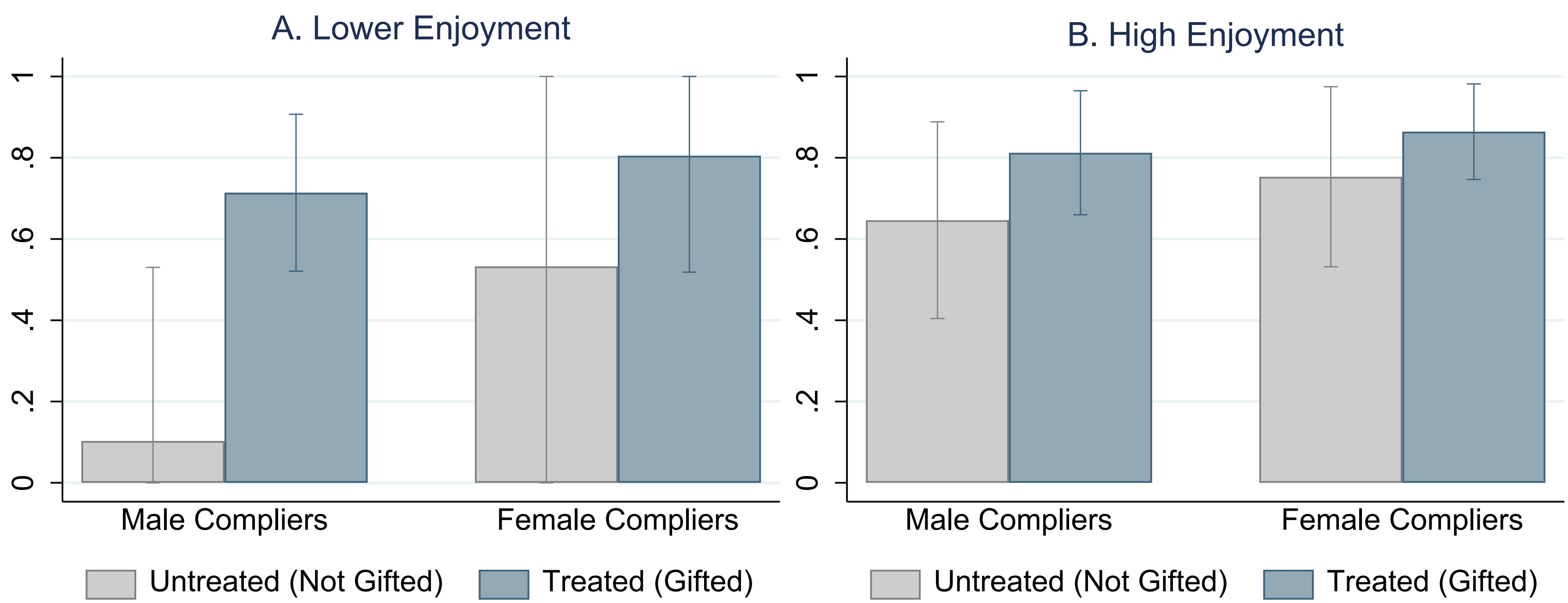
Note: This figure plots reduced-form estimates from local linear RD models with varying bandwidths (IQ points) to the left and right of the gifted eligibility threshold, separately for boys (Panel A) and girls (Panel B). The dependent variable is an indicator for graduating from high school on time and entering college within one year. All models exclude IQ scores that fall in the "donut" region (114-116).

Figure 6: On-Time Graduation & College Entry, Gifted and Non-Gifted Compliers



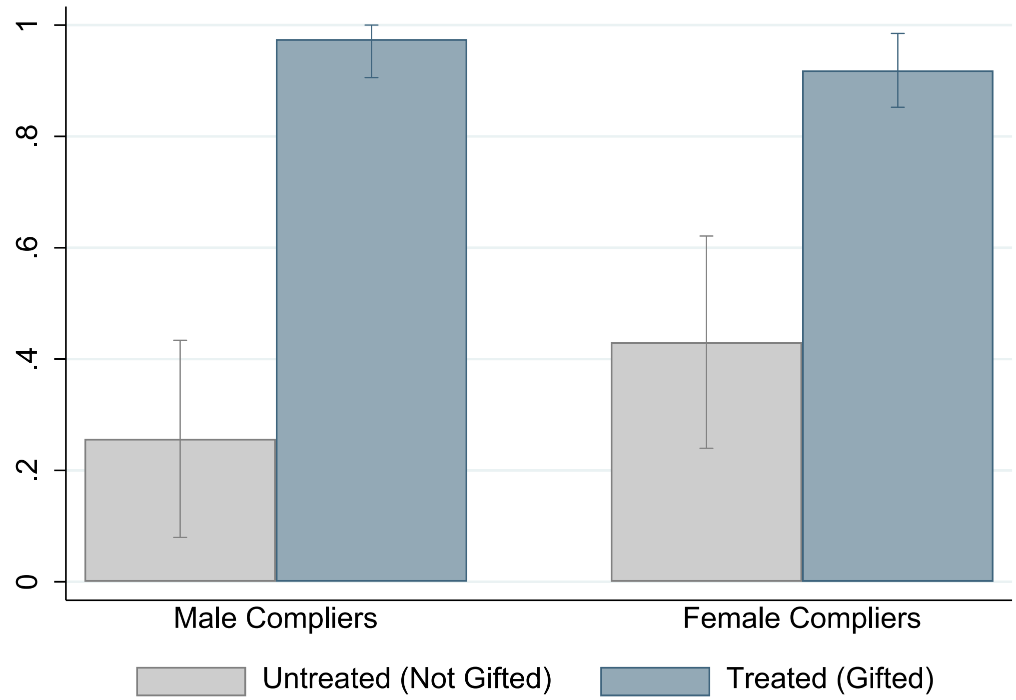
Note: This figure shows the estimated probabilities of graduating high school on time and entering college within one year for gifted and non-gifted compliers. The estimates are constructed following the approach of Abadie (2002). Specifically, complier untreated outcomes are calculated using a linear RD IV specification where the dependent variable is specified as the interaction between on-time graduation and college enrollment and an indicator for not being gifted. Complier treated outcomes are calculated similarly where the dependent variable is an interaction between the outcome and an indicator for gifted status. All estimates are constructed using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116).

Figure 7: On-Time Graduation & College Entry, Gifted and Non-Gifted Compliers
By Gender and Enjoyment of Learning in Grade 3



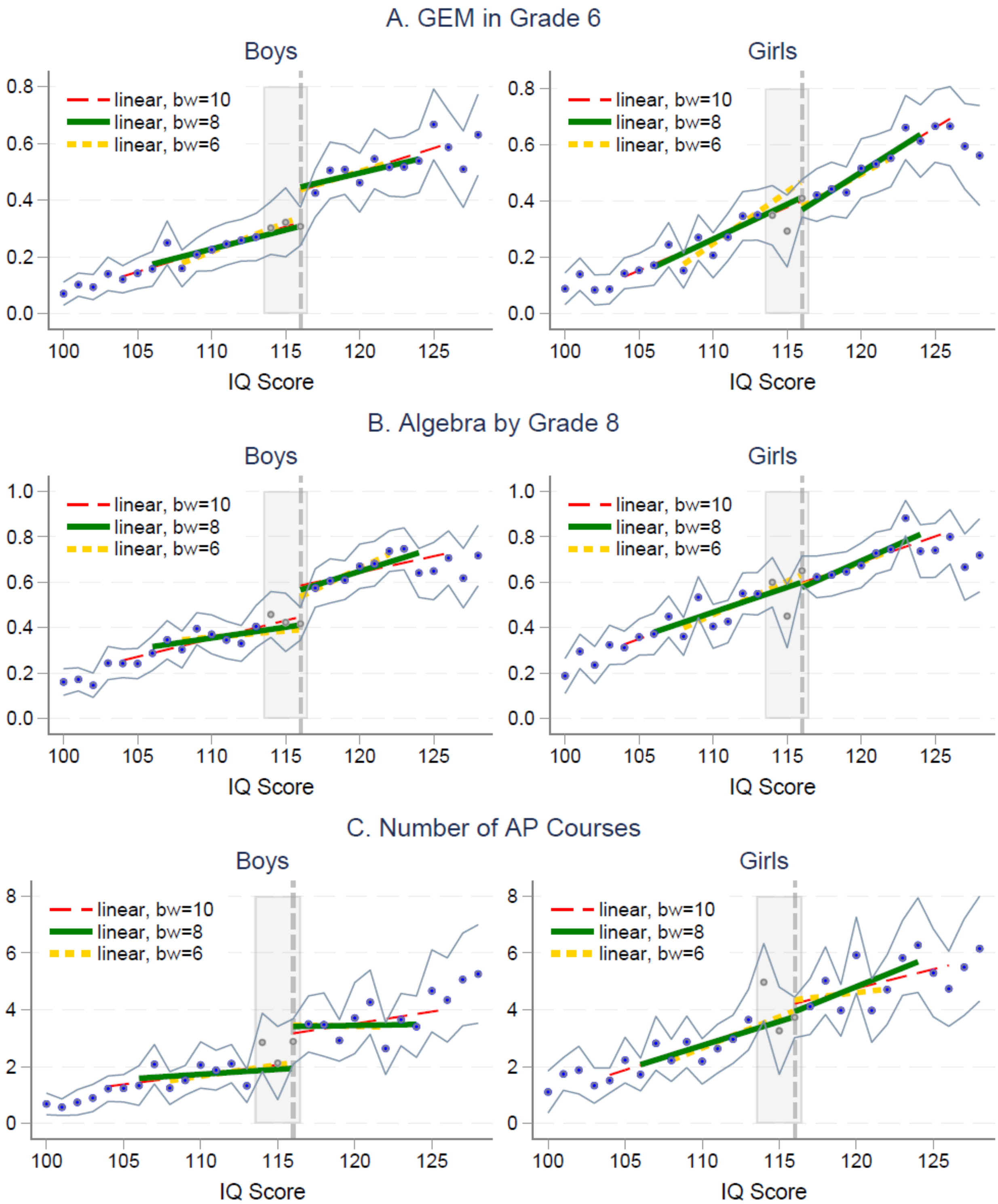
Note: This figure shows the estimated probabilities of graduating high school on time and entering college within one year for gifted and non-gifted compliers. The sample is stratified by students' responses to a District-administered survey asking whether they agree with the statement: "I enjoy learning at my school." Panel A uses students who did not "strongly agree" (N=1,013 boys and 724 girls); Panel B uses those who did strongly agree (N=1,456 boys and 1,486 girls). The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.)

Figure 8: Participation in Gifted/High Achiever Classrooms in Grade 4, Gifted and Non-Gifted Compliers



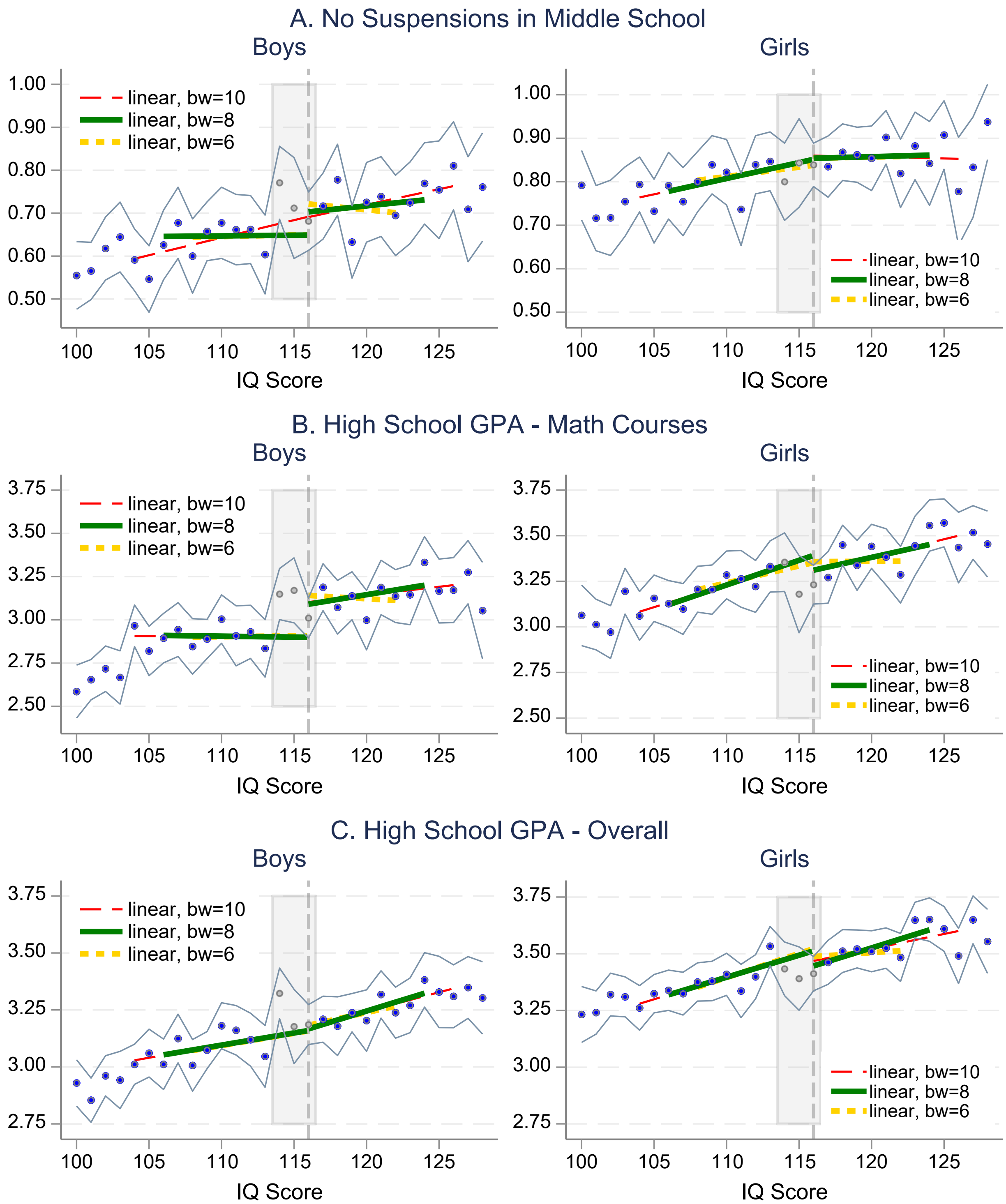
Note: This figure shows the estimated probabilities of participating in a Gifted/High Achiever Classroom in 4th grade for gifted and non-gifted compliers. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.)

Figure 9: Reduced-Form Relationships for Advanced Course Selection



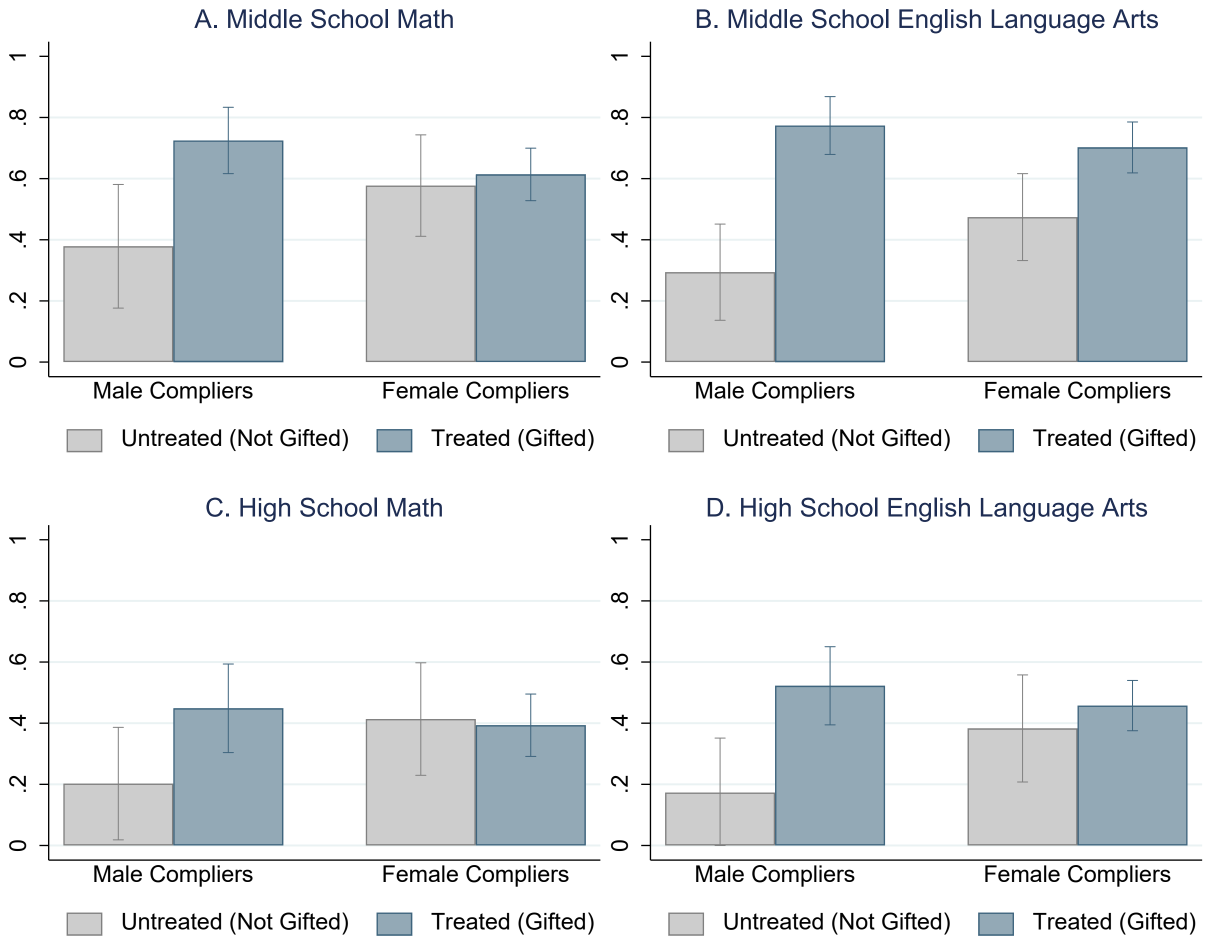
Note: Each panel plots sample means (blue dots) of the dependent variable at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles.

Figure 10: Reduced-Form Relationships for Middle-School Suspensions and High-School Grades



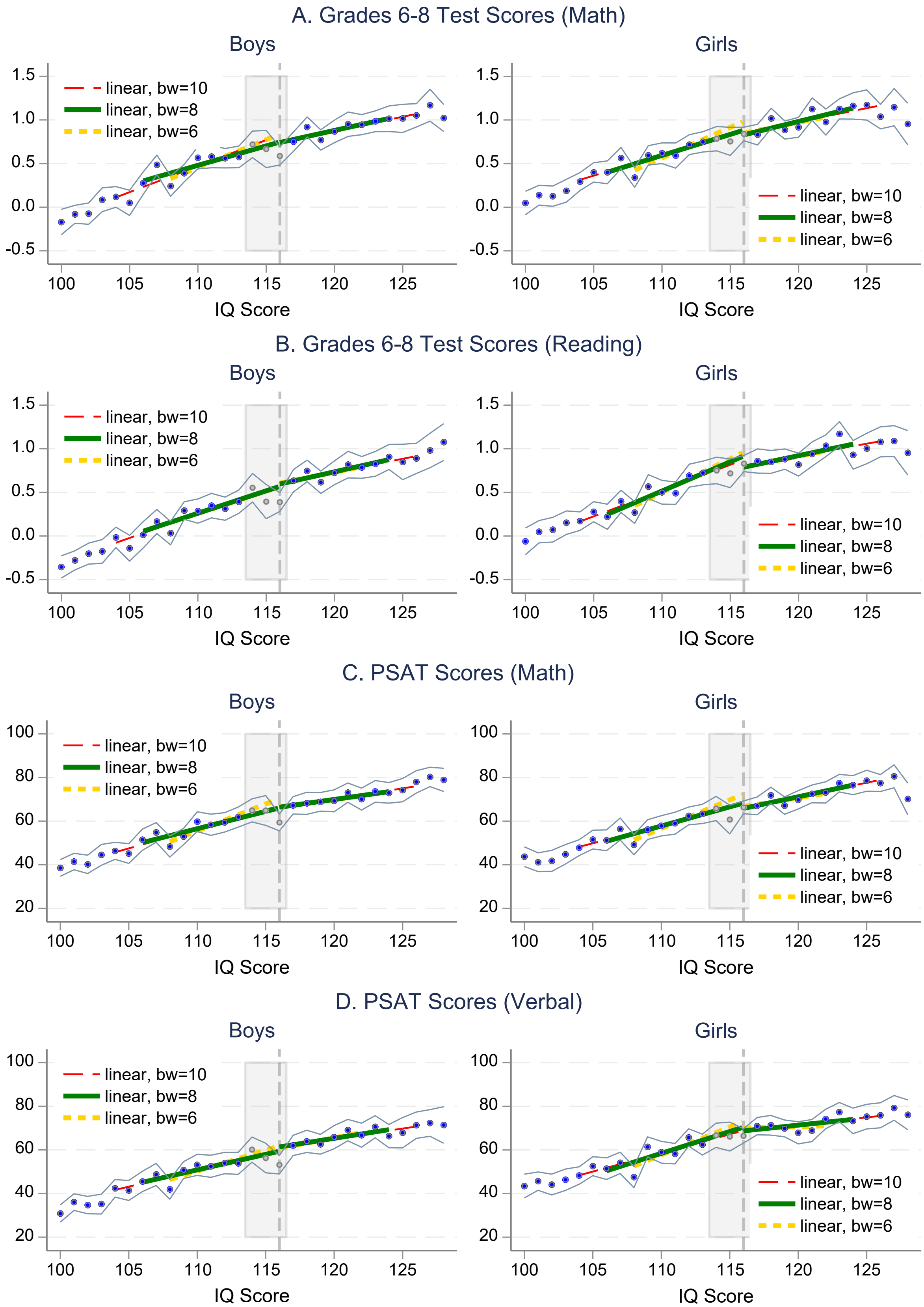
Note: Each panel plots sample means (blue dots) of the dependent variable at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles.

**Figure 11: Classroom Peer Quality in Middle and High School,
Gifted and Non-Gifted Compliers**



Note: This figure shows the estimated average quality of classroom peers—measured by average test scores from grades 3-5—for gifted and non-gifted compliers, separately by gender and school level. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the “donut” region (i.e., scores 114-116). (See notes to Figure 6 for details.)

Figure 12: Reduced-Form Relationships for Standardized Test Scores



Note: Each panel plots sample means (blue dots) of the dependent variable at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles.

Table 1. Summary Statistics, Students in the District

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Plan B + IQ Scores 106-124			Compliers	
	Students	Pooled	Boys	Girls	Boys	Girls
	Panel A. Student Characteristics					
White	0.32	0.18	0.17	0.18	0.15	0.28
					(0.04)	(0.05)
Black	0.35	0.37	0.34	0.39	0.32	0.36
					(0.06)	(0.06)
Hispanic	0.26	0.37	0.40	0.34	0.38	0.29
					(0.06)	(0.05)
FRL	0.49	0.80	0.78	0.83	0.78	0.84
					(0.05)	(0.05)
ELL	0.08	0.05	0.06	0.04	0.03	0.03
					(0.02)	(0.01)
G2 Avg. Test *z*-score	0.03	0.53	0.45	0.62	0.94	0.90
					(0.08)	(0.07)
G2 Math Test *z*-score	0.03	0.57	0.58	0.56	1.07	0.80
					(0.09)	(0.09)
G2 Reading Test *z*-score	0.04	0.49	0.32	0.68	0.81	1.00
					(0.10)	(0.08)
G3 Avg. Test *z*-score	0.06	0.59	0.54	0.65	0.86	0.91
					(0.07)	(0.06)
G3 Math Test *z*-score	0.06	0.66	0.65	0.67	0.99	0.90
					(0.08)	(0.07)
G3 Reading Test *z*-score	0.07	0.52	0.42	0.64	0.74	0.93
					(0.08)	(0.08)
G3, Enjoy Learning at School	4.45	4.48	4.41	4.56	4.29	4.80
(1=least; 5=most)					(0.11)	(0.10)
	Panel B. Students' School Characteristics					
Share Black	0.35	0.38	0.37	0.40	0.39	0.46
					(0.05)	(0.04)
Share Hispanic	0.26	0.26	0.27	0.26	0.24	0.24
					(0.02)	(0.02)
Share FRL	0.49	0.56	0.55	0.57	0.54	0.62
					(0.04)	(0.03)
Avg. Test z-score	0.01	-0.05	-0.04	-0.06	-0.02	-0.12
					(0.05)	(0.04)
Observations	227,754	3,526	1,879	1,647	--	--

Notes: Table entries in columns 1-4 are sample means for all students who were in 5th grade in the District in 2003-2012 (columns 1) and "Plan B" eligible students first IQ scores between 106-124 points, our preferred bandwidth (columns 2-4). Plan B designation is based on FRL and ELL status at the time of an IQ exam. Since the Plan B sample of 5th graders includes students whose first IQ exam was before 5th grade, the FRL and ELL rates do not sum to unity. Columns 5-6 show complier means estimated using a linear RD specification where the outcome is specified as the interaction between the characteristic and gifted status and the sample includes students with IQ scores 104-126 (Abadie, 2002). The bottom row shows the maximum sample size for each column. Information on 2nd-grade test scores is available for ~70 percent of students; survey responses to "enjoy learning" question in 3rd grade are available for ~75 percent of students.

Table 2. Regression Discontinuity Effects for On-time Graduation and College Enrollment

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline (Pre-gifted) Measures			First Stage	Reduced Form	2SLS
	Grade 2, average *z*-score (Math & Reading)	Grade 3, average *z*-score (Math & Reading)	Predicted On-time Enrollment	Probability of being Identified as Gifted	Grad HS On time + Enrolled Within 1 Year	Grad HS On time + Enrolled Within 1 Year
	Panel A. Boys Only					
BW 8	0.11	0.05	0.00	0.52**	0.14**	0.28**
	(0.11)	(0.09)	(0.02)	(0.05)	(0.05)	(0.10)
Obs.	1,285	1,819	1,879	1,879	1,879	1,879
BW 6	-0.04	-0.02	0.00	0.47**	0.19**	0.41**
	(0.14)	(0.12)	(0.03)	(0.05)	(0.07)	(0.16)
Obs.	1,000	1,406	1,451	1,451	1,451	1,451
BW 10	-0.01	-0.00	-0.00	0.51**	0.09*	0.18*
	(0.09)	(0.07)	(0.02)	(0.04)	(0.04)	(0.09)
Obs.	1,595	2,264	2,336	2,336	2,336	2,336
	Panel B. Girls Only					
BW 8	-0.05	-0.07	-0.01	0.60**	0.03	0.05
	(0.10)	(0.08)	(0.01)	(0.04)	(0.06)	(0.09)
Obs.	1,166	1,612	1,647	1,647	1,647	1,647
BW 6	-0.14	-0.21+	-0.01	0.62**	0.04	0.07
	(0.13)	(0.11)	(0.02)	(0.05)	(0.08)	(0.12)
Obs.	915	1,264	1,294	1,294	1,294	1,294
BW 10	-0.03	-0.10	-0.03*	0.61**	0.02	0.03
	(0.10)	(0.07)	(0.01)	(0.04)	(0.05)	(0.08)
Obs.	1,440	2,008	2,048	2,048	2,048	2,048

Notes: This table presents estimates from local linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). The column label at the top indicates the dependent variable in each specification. In columns 1-5, the entries are coefficients on an indicator for having an IQ score ≥ 116. Column 6 shows 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument for gifted status. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 3. Regression Discontinuity Effects for Advanced Course Selection in Elementary, Middle, and High-School

	(1) In GHA Classroom	(2) GEM Eligible	(3) GEM in 6^{th} Grade	(4) Algebra by 8^{th} Grade	(5) # AP Courses
			Panel A. Boys Only		
BW 8	0.72**	0.11	0.26*	0.30**	2.47**
	(0.10)	(0.12)	(0.10)	(0.10)	(0.88)
Obs.	1,506	1,590	1,879	1,879	902
BW 6	0.82**	0.12	0.20	0.31*	2.51+
	(0.14)	(0.17)	(0.14)	(0.15)	(1.28)
Obs.	1,176	1,236	1,451	1,451	683
BW 10	0.70**	0.08	0.22**	0.27**	1.81*
	(0.09)	(0.10)	(0.08)	(0.08)	(0.75)
Obs.	1,874	1,963	2,336	2,336	1,122
			Panel B. Girls Only		
BW 8	0.49**	-0.05	-0.07	-0.04	0.26
	(0.11)	(0.11)	(0.10)	(0.10)	(0.88)
Obs.	1,360	1,413	1,647	1,647	715
BW 6	0.45**	-0.13	-0.14	-0.08	0.53
	(0.13)	(0.12)	(0.11)	(0.12)	(1.00)
Obs.	1,077	1,117	1,294	1,294	543
BW 10	0.55**	0.04	-0.04	-0.02	0.61
	(0.08)	(0.10)	(0.09)	(0.09)	(0.75)
Obs.	1,693	1,745	2,048	2,048	897

Notes: This table presents estimates from local linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. Enrollment in GHA classrooms is only available for the cohorts from 2006-2012. GEM eligibility is only measured for students who have fifth grade standardized math achievement scores. The number of AP courses in high school grades is only available for the cohorts 2003-2007 and 2012. Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 4. Regression Discontinuity Effects for Course Grades and Disciplinary Actions

	(1) G6-G8 Math GPA	(2) G6-G8 No Suspensions	(3) HS Math GPA	(4) HS Lang. Arts GPA	(5) HS Overall GPA
	Panel A. Boys Only				
BW 8	0.17	0.10	0.37+	0.11	0.01
	(0.15)	(0.10)	(0.20)	(0.19)	(0.16)
Obs.	1,879	1,879	1,879	1,879	1,879
BW 6	0.10	0.15	0.50+	0.31	0.05
	(0.21)	(0.14)	(0.28)	(0.26)	(0.23)
Obs.	1,451	1,451	1,451	1,451	1,451
BW 10	0.04	-0.00	0.40*	0.05	0.02
	(0.14)	(0.09)	(0.17)	(0.15)	(0.14)
Obs.	2,336	2,336	2,336	2,336	2,336
	Panel B. Girls Only				
BW 8	-0.10	0.00	-0.13	0.01	-0.11
	(0.12)	(0.08)	(0.16)	(0.11)	(0.10)
Obs.	1,647	1,647	1,647	1,647	1,647
BW 6	-0.07	0.03	0.01	0.03	-0.06
	(0.13)	(0.08)	(0.18)	(0.15)	(0.13)
Obs.	1,294	1,294	1,294	1,294	1,294
BW 10	-0.01	0.02	-0.12	0.01	-0.08
	(0.10)	(0.07)	(0.13)	(0.09)	(0.09)
Obs.	2,048	2,048	2,048	2,048	2,048

Notes: This table presents estimates from local linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 5. Regression Discontinuity Effects for Middle and High School Peer Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	G6 Chall. Courses	G6-G8 Peers, All	G6-G8 Peers, Math Courses	G6-G8 Peers, Reading Courses	HS Peers, All	HS Peers, Math Courses	HS Peers, Reading Courses
	Panel A. Boys Only						
BW 8	0.89+	0.32**	0.35**	0.48**	0.20*	0.25*	0.35**
	(0.49)	(0.08)	(0.11)	(0.09)	(0.10)	(0.12)	(0.11)
Obs.	729	1,879	1,879	1,839	902	902	901
BW 6	1.26+	0.31*	0.23	0.52**	0.08	0.10	0.25
	(0.71)	(0.13)	(0.17)	(0.14)	(0.14)	(0.17)	(0.15)
Obs.	574	1,451	1,451	1,422	683	683	682
BW 10	0.71+	0.24**	0.22*	0.40**	0.12+	0.11	0.24**
	(0.42)	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)	(0.09)
Obs.	897	2,336	2,336	2,283	1,122	1,122	1,121
	Panel B. Girls Only						
BW 8	1.60**	0.14*	0.04	0.23**	0.07	-0.02	0.07
	(0.50)	(0.07)	(0.09)	(0.08)	(0.08)	(0.10)	(0.09)
Obs.	678	1,647	1,646	1,624	715	715	715
BW 6	1.49*	0.04	-0.09	0.11	0.08	-0.04	0.09
	(0.61)	(0.08)	(0.12)	(0.10)	(0.09)	(0.11)	(0.10)
Obs.	553	1,294	1,293	1,279	543	543	543
BW 10	1.25**	0.12*	0.02	0.22**	0.02	-0.05	0.04
	(0.38)	(0.06)	(0.08)	(0.07)	(0.06)	(0.08)	(0.07)
Obs.	840	2,048	2,047	2,015	897	897	897

Notes: This table presents estimates from linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. The grade 6 challenging course survey question in Column 1 is only measured for students in the 2008-2012 cohorts that participated in the survey. The peer measures for high school grades (Columns 5-7) are only available for the cohorts 2003-2007 and 2012. Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 6. Regression Discontinuity Effects for Middle and High-School Test Scores

	(1) G6-G8 Math Scores	(2) G6-G8 Reading Scores	(3) PSAT Math (Percentile)	(4) PSAT Reading (Percentile)
	Panel A. Boys Only			
BW 8	-0.01	0.05	0.60	3.63
	(0.15)	(0.17)	(5.86)	(6.14)
Obs.	1,878	1,879	1,709	1,709
BW 6	-0.21	0.08	-7.74	-2.12
	(0.23)	(0.25)	(8.28)	(8.43)
Obs.	1,450	1,451	1,329	1,329
BW 10	-0.16	0.04	-2.00	3.23
	(0.14)	(0.14)	(5.56)	(5.20)
Obs.	2,335	2,336	2,117	2,117
	Panel B. Girls Only			
BW 8	-0.09	-0.21	-4.06	-2.79
	(0.13)	(0.14)	(4.45)	(4.83)
Obs.	1,647	1,647	1,519	1,519
BW 6	-0.22	-0.27	-9.25+	-5.09
	(0.16)	(0.17)	(5.25)	(6.10)
Obs.	1,294	1,294	1,187	1,187
BW 10	-0.04	-0.12	-2.53	-0.43
	(0.11)	(0.11)	(3.81)	(3.74)
Obs.	2,048	2,048	1,872	1,872

Notes: This table presents estimates from linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 7. Gender Gaps for Non-gifted Compliers and the Effects of Gifted Status

	Non-Gifted Complier Outcomes		Effect of Gifted Status:	
	Female Y(0) Mean	Female - Male Y(0) Gap	Effect on Boys	Differential Effect on Boys
	(1)	(2)	(3)	(4)
	Panel A. Non-Cognitive Outcomes			
Gifted/High-Achieving Classroom Enrollment	0.43	0.17	0.72**	0.23
GEM Enrollment, 6th Grade	0.49	0.23	0.26*	0.34**
G6-G8 Peers, Math Courses (σ units)	0.58	0.20	0.35**	0.31**
G6-G8 Peers, Reading Courses (σ units)	0.47	0.18	0.48**	0.25**
Algebra Enrollment, by 8th Grade	0.67	0.25	0.30**	0.33**
G6-G8, No Suspensions	0.85	0.18	0.10	0.10
HS Peers, Math Courses (σ units)	0.41	0.21	0.25*	0.27*
HS Peers, Reading Courses (σ units)	0.38	0.21	0.35**	0.27*
HS Math GPA	3.46	0.65	0.37+	0.50**
HS Lang. Arts GPA	3.68	0.46	0.11	0.11
HS GPA	3.58	0.34	0.01	0.12
Number of AP Courses	3.94	1.81	2.47**	2.21*
	Panel B. Cognitive Outcomes			
G6-G8 Test Scores (σ units)	1.04	0.25	0.04	0.20
G6-G8 Math Test Scores (σ units)	0.96	0.04	-0.01	0.08
G6-G8 Reading Test Scores (σ units)	1.12	0.43	0.05	0.27
PSAT (Percentile)	71.69	6.32	0.45	2.54
PSAT Math (Percentile)	71.32	0.01	0.60	4.66
PSAT Reading (Percentile)	75.93	13.9	3.63	6.42
	Panel C. College Outcomes			
Grad HS On Time + Enroll Within 1 Year	0.74	0.28	0.28**	0.23

Notes: Each row reports summary statistics for the education outcome described in the first column for students in our main analysis sample. Column 1 reports estimated means of the outcome for girl compliers if they had not been exposed to treatment (i.e., the estimated means of Y(0), in standard notation). Column 2 reports the difference in estimated means of the complier untreated outcomes (i.e., the gender gap in Y(0) between girls and boys). Column 3 shows the estimated effect for boys of achieving gifted status by the end of 5th grade on the outcome. Column 4 shows the difference in the estimated effects for boys relative to girls. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Statistical significance of estimated effects in columns 3-4 is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

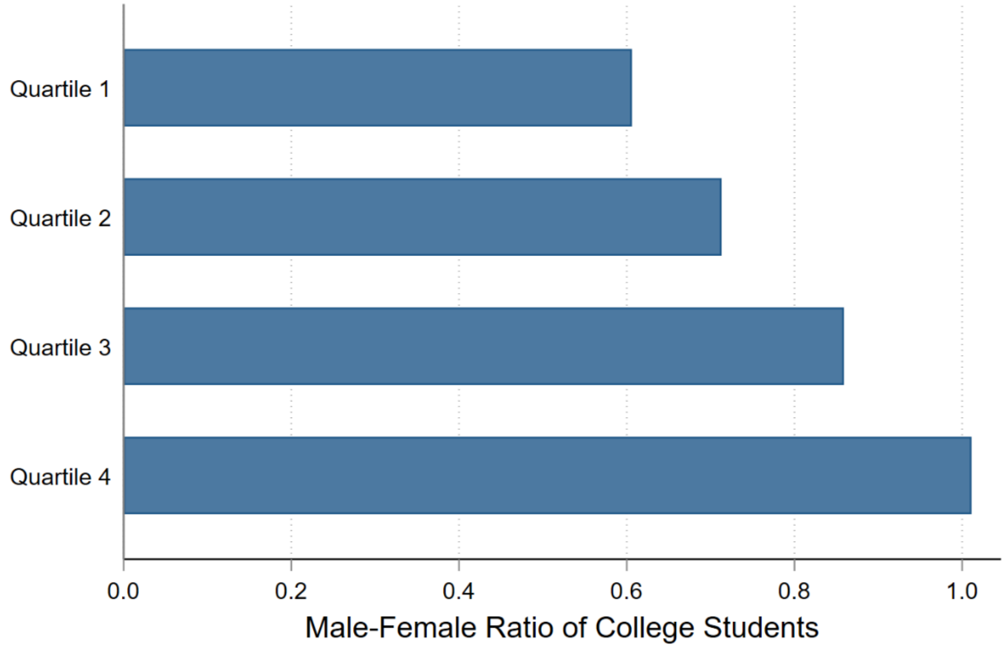
Online Appendix

Can Gifted Education Help Higher-Ability Boys from Disadvantaged Backgrounds?

David Card, Eric Chyn, and Laura Giuliano

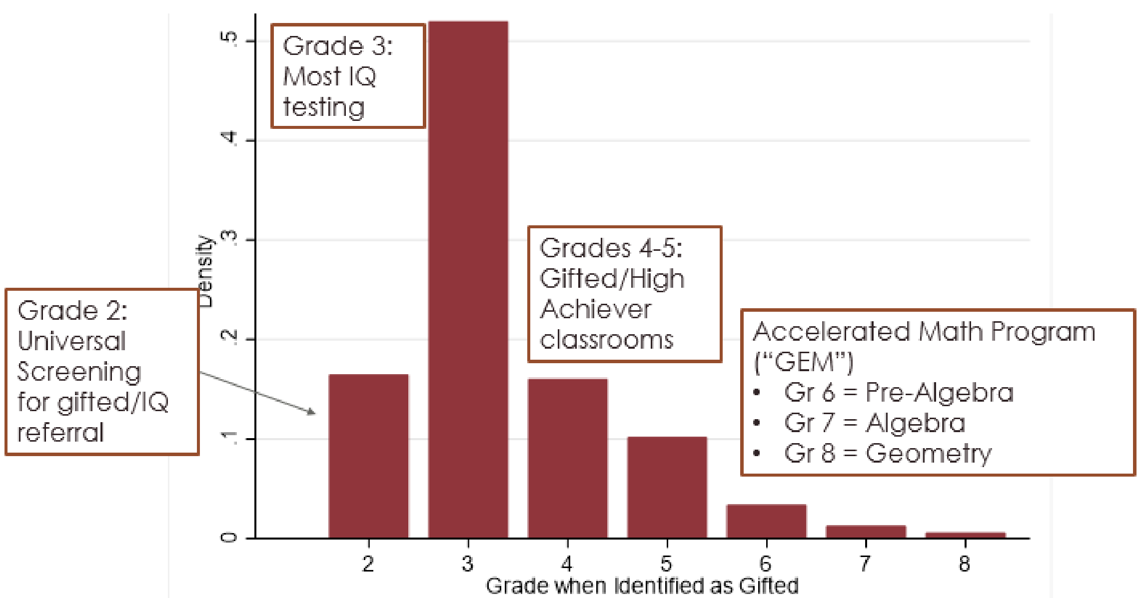
Appendix A: Additional Figures and Tables

Figure A1: Male-Female Ratio of College Freshmen by Family Income Quartile



Source: U.S. Department of Education, National Center for Education Statistics, 1995-96 National Postsecondary Student Aid Study (NPSAS:96), NPSAS:2000, NPSAS:04, NPSAS:08, NPSAS:12 and NPSAS:16. Computation by NCES TrendStats on 8/28/2021.

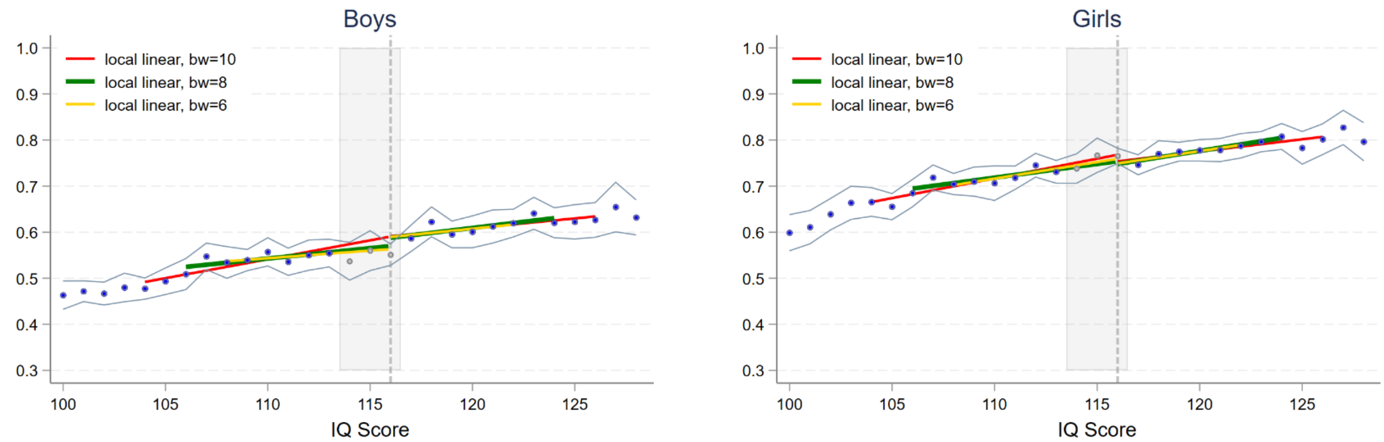
Figure A2: Timing of Gifted Screening, Identification, and Relevant Programs



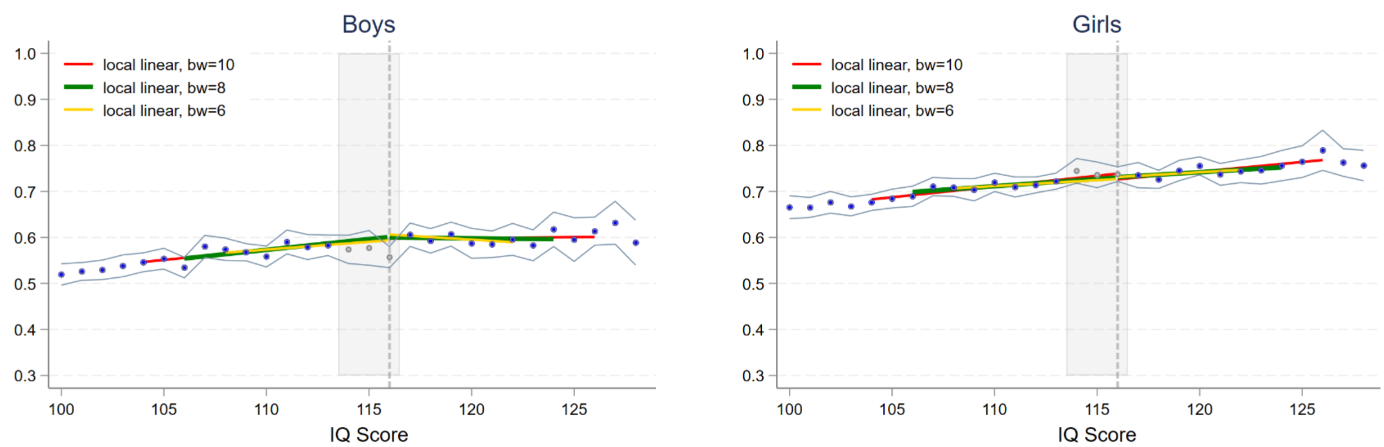
Notes: This figure is a histogram of the grade when a student was identified as gifted for the sample of all gifted students who were in 5th grade in the District between 2003-2012 (the cohorts in our analysis sample) and who were FRL participants or English Language Learners (i.e., "Plan B" eligible) at the time of their first IQ test. Information on the timing of relevant educational policies and programs is also illustrated.

Figure A3: Reduced-Form Relationships, Predicted On-Time Graduation and College Enrollment Using Second-Grade Test Scores

A. Using 2nd-grade SAT scores



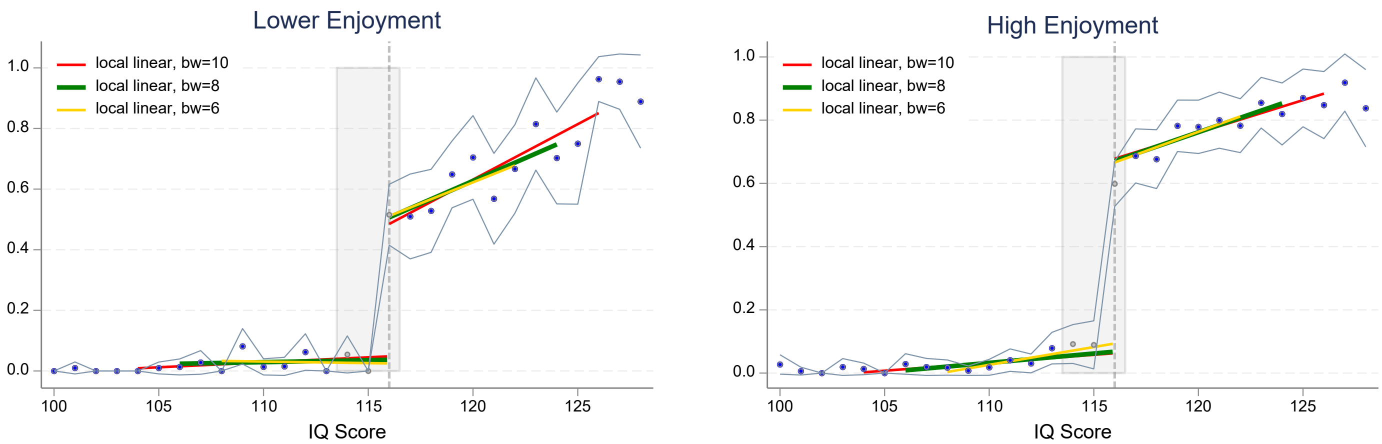
B. Using 2nd-grade Nonverbal Ability Index



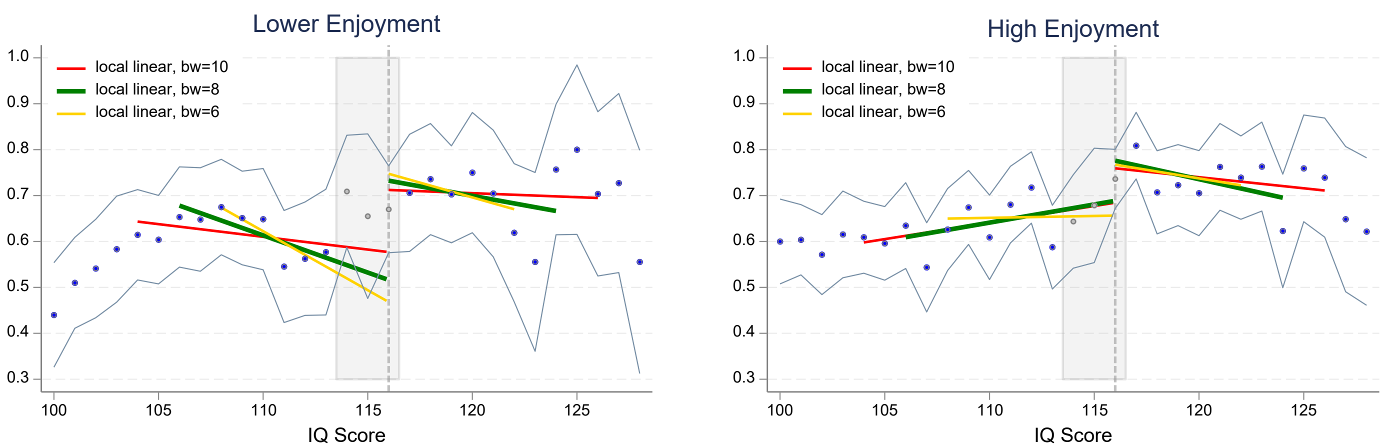
Notes: This figure plots sample means (blue dots) of predicted enrollment at each value of IQ, for boys (Panel A) and girls (Panel B), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles. The dependent variable is predicted probability of graduating on time and enrolling in college from models fit separately to boys and girls with IQ scores in the range from 100 to 115. The prediction models are similar to those used in Panel B of Figure 4 but replace 3rd-grade scores with either 2nd-grade SAT scores in math and reading (Panel A) or 2nd-grade Nonverbal Ability Index based on the test used for gifted screening in 2nd grade (Panel B). The models also include students' responses in grade 3 to a survey question about how much they enjoy learning in their school; the number of internal and external suspensions in grade 3; indicators for student race/ethnicity, FRL status, ELL status, and cohort; average test scores, fraction FRL and fraction nonwhite of the school where the student is enrolling in grade 5; and the median household income of the student's neighborhood.

Figure A4: First-Stage and Reduced-Form Relationships for On-Time College Enrollment, Boys and Girls with Low vs. High Enjoyment of Learning in Grade 3

A. First Stage Relationships for Gifted Status

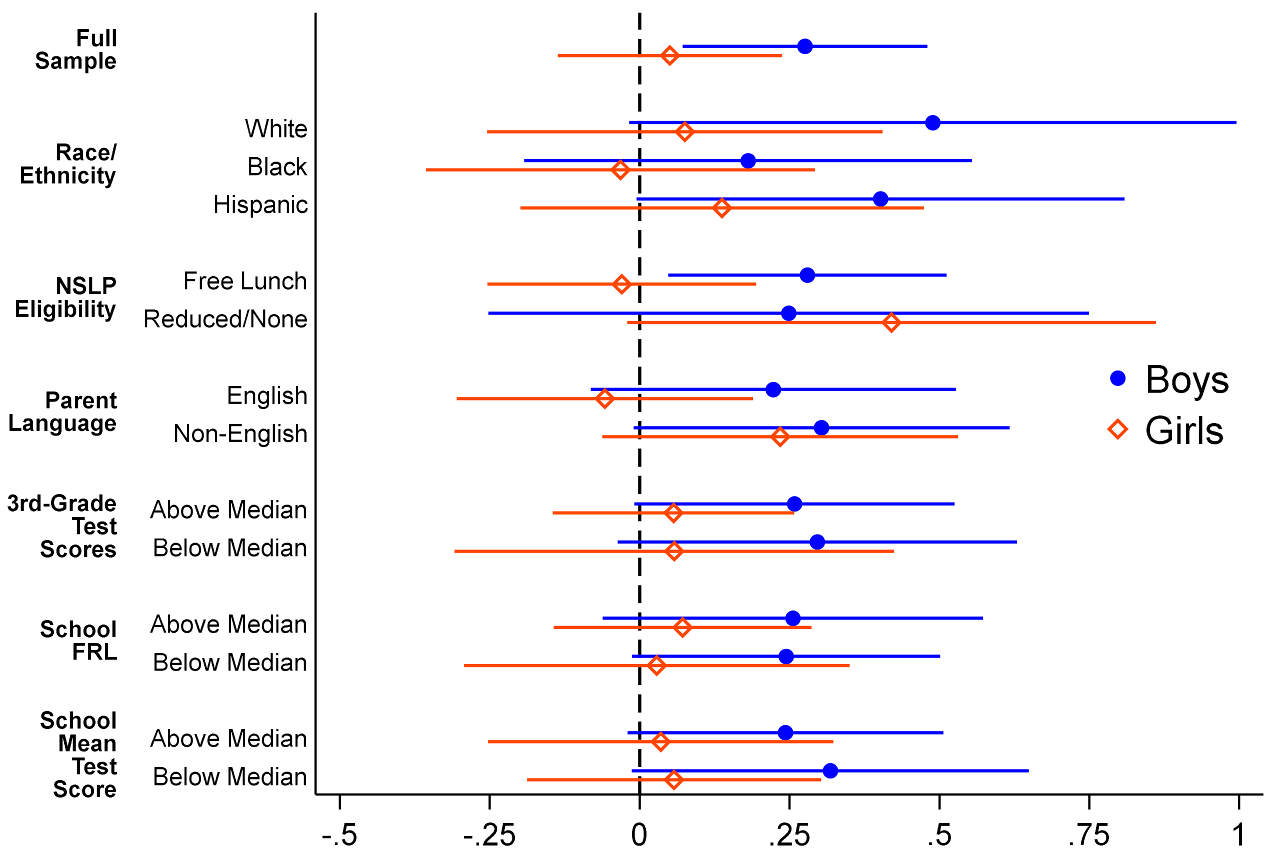


B. Reduced-Form Relationships for On-Time College Enrollment



Notes: This figure plots sample means (blue dots) of the dependent variable at each value of IQ for two samples along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the “donut” region (114-116); the means for IQ scores in this region are indicated by open circles. In Panel A, the dependent variable is an indicator for gifted status (as of the end of 5th grade); in Panel B, it is an indicator for graduating high school on time and enrolling in college within one year. Each panel shows plots for two samples: the figures on the left use boys and girls with low non-cognitive skills in 3rd grade and those on the right use boys and girls with high non-cognitive skills. As in Figure 7, students are classified as having “high enjoyment” if, in response to a District-administered survey, they “strongly agreed” that they enjoyed learning at their school.

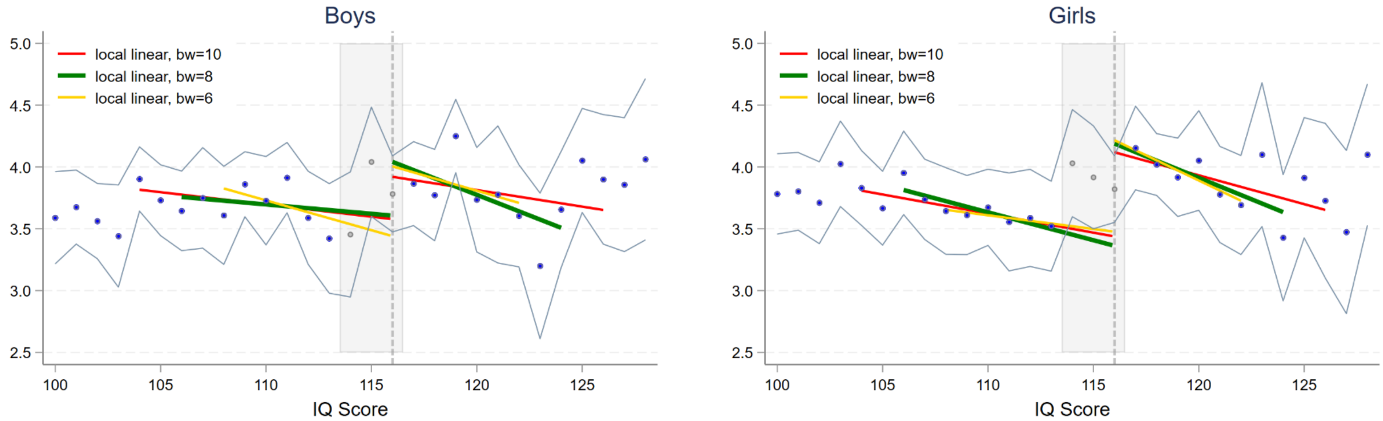
Figure A5: Other Potential Sources of Treatment Effect Heterogeneity



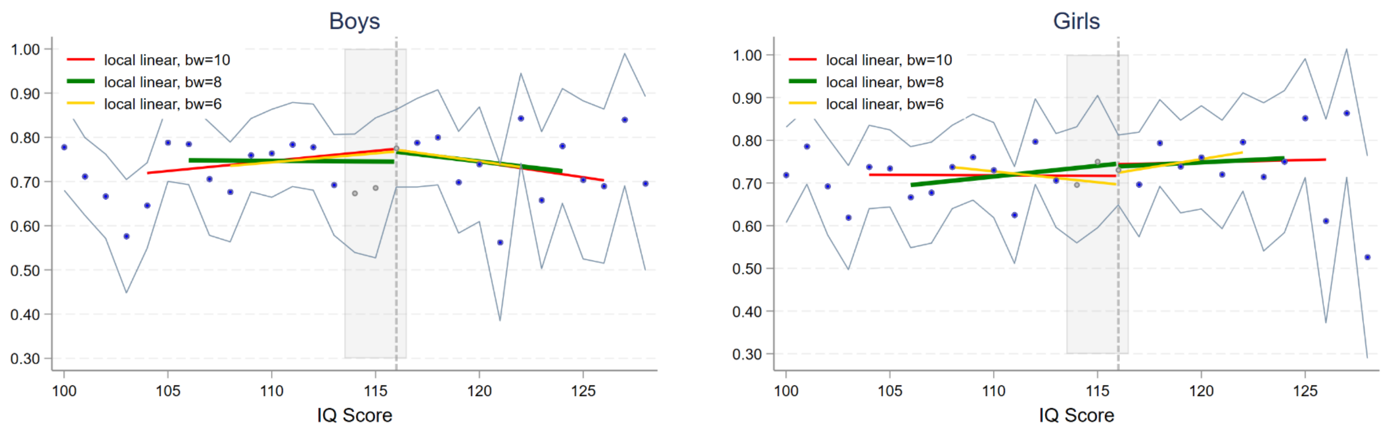
Notes: This figure reports 2SLS estimates from local linear fuzzy RD models where the endogenous variable is gifted status. All models use a symmetric bandwidth of 8 (IQ scores between 106-124) and exclude IQ scores that fall in the "donut" region (scores between 114-116). Point estimates for the effect of gifted status are presented by subgroup (as indicated in the row labels) separately for boys (blue, circle marker) and girls (orange, diamond marker). The lines represent 95% confidence intervals for the respective estimates.

Figure A6: Reduced-Form Relationships, Survey Response on Guidance with Selecting Challenging Courses

A. Response on Scale from 1 (Strongly Disagree) to 5 (Strongly Agree)



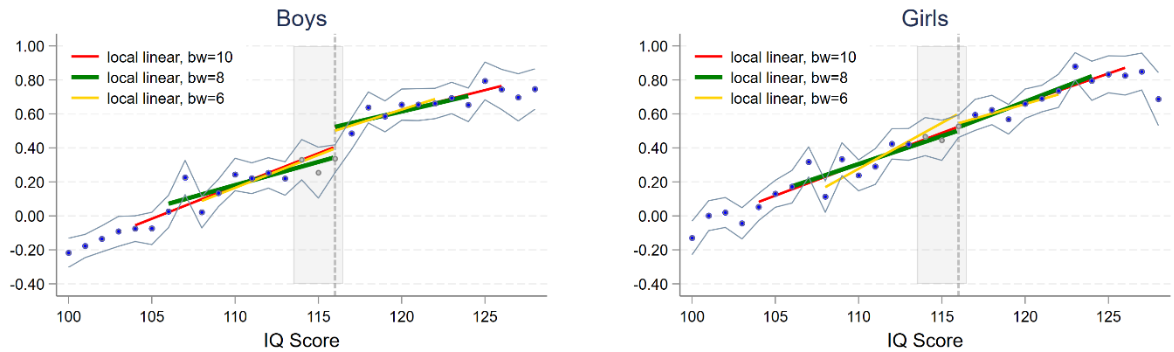
B. Probability of Non-Missing Response



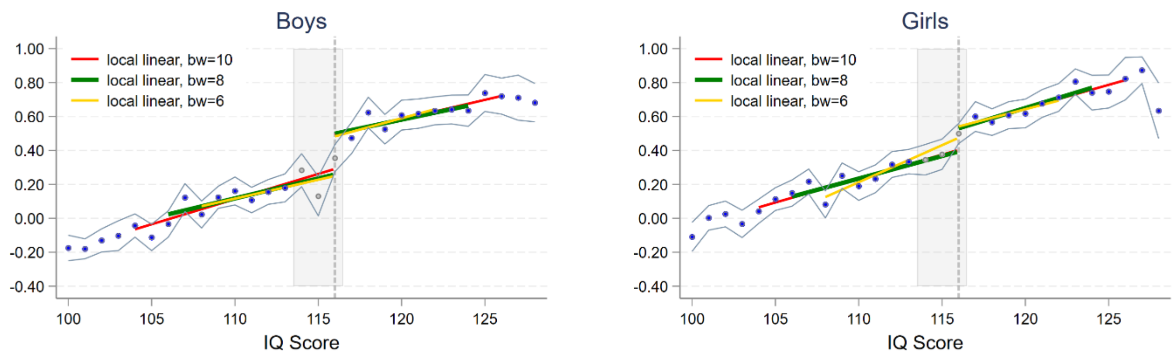
Notes: This figure plots sample means (blue dots) of the dependent variable at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles. The dependent variable in the top row (Panel A) is the survey response of 6th graders, collected on a 5-point Likert scale measuring agreement with the statement: "This year, school staff helped me to select high level courses that challenge my abilities." The student questionnaire was only collected in the 2008-2011 5th grade cohorts, so this analysis is based only on students in these four cohorts who had non-missing responses. In Panel B, the dependent variable is an indicator for having a non-missing response; the analysis sample is again limited to the four cohorts who received the survey.

Figure A7: Reduced-Form Relationships, Peer Quality in Middle and High School Courses

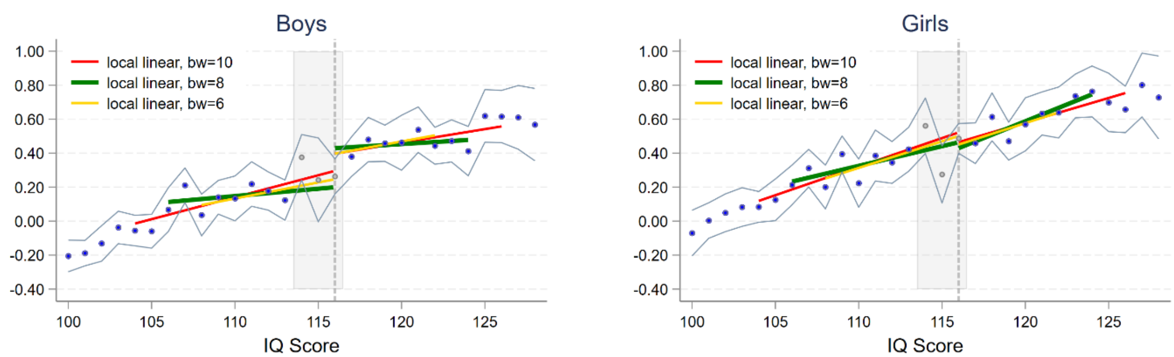
A. Middle School Math Courses



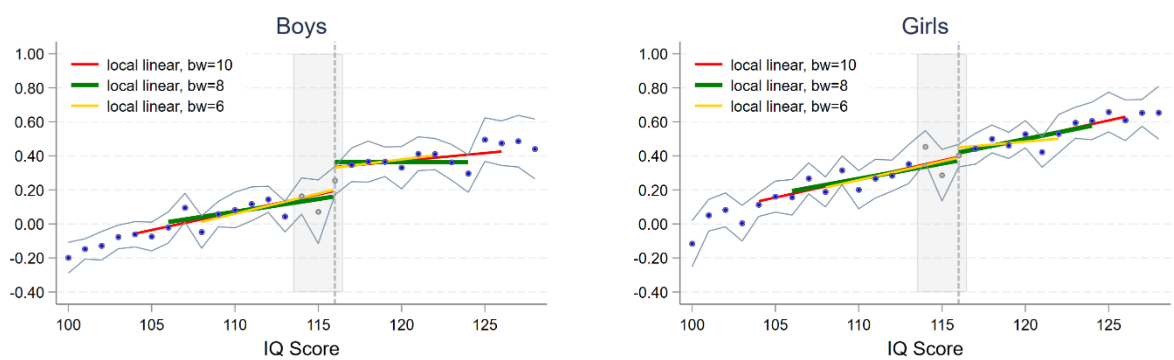
B. Middle School English Language Arts Courses



C. High School Math Courses



D. High School English Language Arts Courses



Notes: This figure plots sample means (blue dots) of classmate (peer) quality, as represented by their mean test scores in grades 3-5, in the set of classed indicated in the panel heading, at each value of IQ, for boys (left) and girls (right), along with 95% confidence intervals for the means (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 10 (red), 8 (green), or 6 (yellow). All models are estimated excluding IQ scores that fall in the "donut" region (114-116); the means for IQ scores in this region are indicated by open circles. The peer measures for high school grades in panels C and D are only available for the cohorts 2003-2007 and 2012.

Appendix Table A1. Characteristics of Compliers with Participation in Gifted/High Achiever Classroom in Grade 4

	(1) Plan B Gifted; (Not High Achievers)	(2) Non- Gifted High Achievers	(3) Minority Non-Gifted High Achievers
<u>*Own characteristics*</u>:			
Grade 3 reading	0.62	0.90	0.84
Grade 3 math	0.81	0.84	0.64
Female	0.44	0.52	0.58
Black	0.44	0.22	0.51
Hispanic	0.29	0.21	0.49
FRL	0.91	0.29	0.04
ELL	0.19	0.01	0.03
Neighborhood Median Household Income	48.3	64.5	54.0
Non-Verbal Ability Index (NNAT)	124.9	86.6	93.1
Enjoy Learning at School, Gr 3 (1=least, 5=most)	4.40	4.54	4.55
<u>*Classroom characteristics*</u>:			
Avg Gr 3 reading of Gr 4 classroom	0.65	0.95	0.87
Avg Gr 3 math of Gr 4 classroom	0.67	0.92	0.78
Classroom % gifted	0.53	0.31	0.26

Notes: This table presents estimates of the mean characteristics of gifted and non-gifted compliers with the treatment defined as being placed in a separate "gifted/high achiever" classroom in grade 4, as well as mean characteristics of their classroom peers. Column 1 shows characteristics of the compliers in our design for disadvantaged gifted students (i.e., with IQ $\geq$ 116) but whose 3rd-grade test scores were below the "high achiever" threshold for their school/cohort. Column 2 shows characteristics of the compliers in the RD design used in Card and Giuliano (2016b) (i.e., non-gifted "high achievers" whose 3rd-grade standardized test scores ranked relatively high within their school/cohort). Column 3 shows characteristics for the subset of compliers in Card and Giuliano (2016b) who were minorities.

Appendix Table A2. Sample Selection Tests

	(1)	(2)	(3)
		Sample	
	Pooled	Boys	Girls
BW 8	-0.01	-0.05	0.03
	(0.03)	(0.05)	(0.04)
Mean Below Threshold	0.731	0.742	0.715
Obs.	5,022	2,749	2,273
BW 6	-0.01	-0.02	0.01
	(0.05)	(0.07)	(0.06)
Mean Below Threshold	0.735	0.737	0.730
Obs.	3,889	2,110	1,779
BW 10	0.01	-0.03	0.06
	(0.03)	(0.04)	(0.04)
Mean Below Threshold	0.713	0.726	0.696
Obs.	6,273	3,448	2,825

Notes: This table presents regression discontinuity estimates of the effect of having IQ ≥116 on an indicator for being included in our estimation sample, among students who were IQ tested by 5th grade. The column label at the top indicates the sample. We show estimates for 3 ranges of IQ: (i) IQ scores in the range 106-124 (BW 8); (ii) 108-122 (BW 6); (iii) 104-126 (BW 10). All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The means of the outcome for students below the 116-point threshold are estimated from the intercepts of the same models. Standard errors are clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix Table A3. Summary Statistics on All Student Outcomes

	(1)	(2)	(3)	(4)	(5)
	Plan B + IQ Scores 106-124			Non-Gifted Compliers	
	Pooled	Boys	Girls	Boys	Girls
Panel A. Non-Cognitive Outcomes					
Gifted/High-Achieving Classroom Enrollment	0.42	0.41	0.44	0.26	0.43
GEM Enrollment, 6th Grade	0.35	0.34	0.36	0.26	0.49
G6-G8 Peers, Math Courses (σ units)	0.31	0.27	0.36	0.28	0.42
G6-G8 Peers, Reading Courses (σ units)	0.31	0.26	0.36	0.29	0.43
Algebra Enrollment, by 8th Grade	0.52	0.48	0.56	0.42	0.67
G6-G8, No Suspensions	0.75	0.68	0.83	0.67	0.85
HS Peers, Math Courses (σ units)	0.23	0.17	0.30	0.18	0.27
HS Peers, Reading Courses (σ units)	0.22	0.16	0.30	0.17	0.28
HS Math GPA	3.14	3.01	3.29	2.81	3.46
HS Lang. Arts GPA	3.41	3.24	3.60	3.22	3.68
HS GPA	3.29	3.16	3.45	3.24	3.58
Number of AP Courses	3.03	2.50	3.70	2.13	3.94
B. Cognitive Outcomes					
G6-G8 Test Scores (σ units)	0.62	0.55	0.70	0.79	1.04
G6-G8 Math Test Scores (σ units)	0.69	0.64	0.75	0.92	0.96
G6-G8 Reading Test Scores (σ units)	0.55	0.45	0.68	0.69	1.12
PSAT (Percentile)	58.98	56.23	62.08	65.37	71.69
PSAT Math (Percentile)	62.56	61.89	63.32	71.31	71.32
PSAT Reading (Percentile)	60.00	56.73	63.67	62.03	75.93
C. College					
Grad HS On Time + Enroll Within 1 Yr.	0.67	0.62	0.72	0.46	0.74
Observations	3,526	1,879	1,647	--	--

Notes: This table presents means of the main outcome variables used in the paper for the samples described in columns 2-6 of Table 1. Entries in columns 1-3 are simple means. Entries in columns 4-5 are complier means, calculated using a linear RD specification where the outcome is specified as the interaction between the characteristic and an indicator for not being gifted and the sample includes students with IQ scores 104-126 (Abadie, 2002). The sample sizes in the bottom row indicate the maximal number of individuals included in the column.

Appendix Table A4. Additional Balance Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline Student Characteristics								Baseline School Characteristics			
	Age	FRL	ELL	White	Black	Hispanic	G3 Reading *z*-score	G3 Math *z*-score	Share Non-White	Share FRL	Median HH Income	Avg. Test Score
Panel A. Boys Only												
BW 8	0.03	-0.01	-0.01	-0.02	-0.08	0.09	0.02	0.08	-0.01	-0.03	-0.53	0.02
	(0.05)	(0.05)	(0.03)	(0.04)	(0.06)	(0.06)	(0.10)	(0.09)	(0.02)	(0.03)	(2.03)	(0.04)
Obs.	1,879	1,879	1,879	1,879	1,879	1,879	1,818	1,817	1,879	1,879	1,867	1,879
BW 6	0.05	0.01	-0.03	-0.09	-0.06	0.11	-0.03	-0.00	0.01	-0.02	-1.04	0.00
	(0.06)	(0.06)	(0.04)	(0.06)	(0.07)	(0.07)	(0.14)	(0.13)	(0.03)	(0.04)	(2.39)	(0.05)
Obs.	1,451	1,451	1,451	1,451	1,451	1,451	1,405	1,405	1,451	1,451	1,441	1,451
BW 10	0.03	0.03	-0.01	-0.02	-0.05	0.03	0.01	-0.02	-0.01	-0.02	-1.28	-0.01
	(0.04)	(0.04)	(0.02)	(0.03)	(0.05)	(0.05)	(0.09)	(0.08)	(0.02)	(0.02)	(1.47)	(0.03)
Obs.	2,336	2,336	2,336	2,336	2,336	2,336	2,263	2,260	2,336	2,336	2,323	2,336
Panel B. Girls Only												
BW 8	-0.00	0.02	-0.01	0.01	0.01	-0.00	-0.07	-0.07	0.01	0.01	0.23	0.03
	(0.05)	(0.05)	(0.02)	(0.05)	(0.06)	(0.06)	(0.10)	(0.09)	(0.02)	(0.03)	(2.01)	(0.04)
Obs.	1,647	1,647	1,647	1,647	1,647	1,647	1,611	1,611	1,647	1,647	1,641	1,647
BW 6	0.00	0.01	-0.02	-0.06	0.07	0.01	-0.20	-0.22+	0.03	0.02	1.82	0.02
	(0.06)	(0.06)	(0.03)	(0.06)	(0.07)	(0.08)	(0.13)	(0.12)	(0.03)	(0.04)	(2.58)	(0.05)
Obs.	1,294	1,294	1,294	1,294	1,294	1,294	1,263	1,263	1,294	1,294	1,288	1,294
BW 10	0.05	0.00	-0.01	-0.00	0.01	0.03	-0.11	-0.10	0.02	0.03	-1.59	-0.00
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)	(0.09)	(0.08)	(0.02)	(0.03)	(1.71)	(0.04)
Obs.	2,048	2,048	2,048	2,048	2,048	2,048	2,006	2,006	2,048	2,048	2,041	2,048

Notes: This table presents estimates from local linear regression discontinuity specifications of the effect of having an IQ score ≥ 116 on the outcome indicated by the column heading. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix Table A5. Discontinuities in Probability of Graduating On-Time and Entering College with Various Bandwidths

A. Boys

Bandwidth on Left	Bandwidth on Right: 3	4	5	6	7	8	9	10	11	12
3	0.320 (0.154)	0.307 (0.150)	0.271 (0.146)	0.247 (0.143)	0.224 (0.143)	0.218 (0.141)	0.203 (0.143)	0.204 (0.144)	0.209 (0.144)	0.212 (0.142)
4	0.292 (0.113)	0.279 (0.108)	0.243 (0.104)	0.219 (0.101)	0.196 (0.100)	0.191 (0.098)	0.176 (0.099)	0.177 (0.100)	0.182 (0.101)	0.185 (0.099)
5	0.293 (0.087)	0.28 (0.081)	0.244 (0.079)	0.22 (0.075)	0.197 (0.074)	0.192 (0.071)	0.177 (0.071)	0.178 (0.074)	0.183 (0.073)	0.186 (0.072)
6	0.265 (0.083)	0.252 (0.076)	0.215 (0.073)	0.192 (0.070)	0.169 (0.069)	0.163 (0.067)	0.148 (0.066)	0.149 (0.068)	0.154 (0.068)	0.157 (0.066)
7	0.268 (0.076)	0.255 (0.070)	0.219 (0.066)	0.195 (0.061)	0.172 (0.060)	0.166 (0.058)	0.152 (0.058)	0.153 (0.059)	0.158 (0.059)	0.161 (0.057)
8	0.245 (0.072)	0.232 (0.067)	0.196 (0.061)	0.172 (0.056)	0.149 (0.055)	0.143 (0.052)	0.129 (0.052)	0.13 (0.053)	0.134 (0.052)	0.138 (0.050)
9	0.212 (0.070)	0.199 (0.065)	0.163 (0.059)	0.139 (0.055)	0.116 (0.053)	0.111 (0.050)	0.096 (0.049)	0.097 (0.050)	0.102 (0.049)	0.105 (0.047)
10	0.208 (0.065)	0.195 (0.060)	0.159 (0.054)	0.135 (0.049)	0.112 (0.047)	0.106 (0.044)	0.092 (0.044)	0.093 (0.045)	0.097 (0.044)	0.100 (0.041)
11	0.201 (0.065)	0.187 (0.059)	0.151 (0.052)	0.128 (0.046)	0.105 (0.046)	0.099 (0.043)	0.084 (0.043)	0.085 (0.044)	0.090 (0.043)	0.093 (0.040)
12	0.191 (0.063)	0.178 (0.057)	0.142 (0.049)	0.119 (0.044)	0.096 (0.042)	0.090 (0.040)	0.075 (0.040)	0.076 (0.041)	0.081 (0.039)	0.084 (0.036)
13	0.175 (0.062)	0.162 (0.056)	0.126 (0.048)	0.103 (0.043)	0.08 (0.040)	0.074 (0.038)	0.059 (0.039)	0.060 (0.038)	0.065 (0.037)	0.068 (0.034)
14	0.166 (0.063)	0.153 (0.056)	0.117 (0.049)	0.093 (0.043)	0.070 (0.041)	0.065 (0.038)	0.050 (0.038)	0.051 (0.038)	0.056 (0.037)	0.059 (0.034)

Notes: This table presents estimates from local linear regression discontinuity specifications of the effect of having an IQ score ≥ 116 on the event of completing high school on time and entering college the next year. The range of IQ's included in the sample to the left of the cutoff is indicated by the row headings; the range to the right is indicated by the column heading. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level.

B. Girls

Bandwidth on Left	Bandwidth on Right: 3	4	5	6	7	8	9	10	11	12
3	0.041	0.056	0.046	0.047	0.039	0.052	0.055	0.057	0.055	0.074
	(0.151)	(0.148)	(0.144)	(0.141)	(0.141)	(0.138)	(0.136)	(0.135)	(0.135)	(0.134)
4	0.031	0.046	0.036	0.037	0.028	0.042	0.045	0.047	0.045	0.064
	(0.111)	(0.102)	(0.101)	(0.097)	(0.097)	(0.094)	(0.091)	(0.090)	(0.091)	(0.091)
5	0.058	0.073	0.062	0.064	0.055	0.069	0.071	0.074	0.072	0.091
	(0.103)	(0.092)	(0.090)	(0.086)	(0.085)	(0.082)	(0.079)	(0.078)	(0.078)	(0.078)
6	0.037	0.052	0.042	0.043	0.035	0.048	0.051	0.053	0.051	0.070
	(0.099)	(0.087)	(0.082)	(0.077)	(0.076)	(0.073)	(0.070)	(0.070)	(0.069)	(0.069)
7	-0.008	0.007	-0.003	-0.002	-0.010	0.004	0.006	0.008	0.007	0.025
	(0.093)	(0.080)	(0.075)	(0.069)	(0.067)	(0.064)	(0.062)	(0.061)	(0.060)	(0.061)
8	0.019	0.034	0.024	0.025	0.017	0.031	0.033	0.035	0.034	0.052
	(0.086)	(0.073)	(0.068)	(0.062)	(0.060)	(0.057)	(0.055)	(0.055)	(0.055)	(0.056)
9	0.010	0.025	0.015	0.016	0.007	0.021	0.024	0.026	0.024	0.043
	(0.083)	(0.071)	(0.065)	(0.059)	(0.058)	(0.054)	(0.052)	(0.051)	(0.051)	(0.052)
10	0.004	0.019	0.009	0.010	0.002	0.015	0.018	0.020	0.018	0.037
	(0.078)	(0.066)	(0.061)	(0.054)	(0.053)	(0.049)	(0.048)	(0.047)	(0.047)	(0.048)
11	0.008	0.023	0.013	0.014	0.005	0.019	0.022	0.024	0.022	0.041
	(0.077)	(0.066)	(0.060)	(0.053)	(0.052)	(0.048)	(0.047)	(0.046)	(0.045)	(0.047)
12	0.006	0.020	0.010	0.012	0.003	0.017	0.019	0.022	0.020	0.039
	(0.076)	(0.064)	(0.059)	(0.052)	(0.050)	(0.046)	(0.045)	(0.044)	(0.043)	(0.045)
13	0.018	0.033	0.023	0.024	0.016	0.030	0.032	0.034	0.033	0.051
	(0.074)	(0.062)	(0.057)	(0.049)	(0.048)	(0.044)	(0.043)	(0.042)	(0.041)	(0.042)
14	0.009	0.024	0.014	0.015	0.007	0.020	0.023	0.025	0.023	0.042
	(0.072)	(0.061)	(0.055)	(0.048)	(0.046)	(0.043)	(0.042)	(0.041)	(0.040)	(0.042)

Notes: This table presents estimates from local linear regression discontinuity specifications of the effect of having an IQ score ≥ 116 on the event of completing high school on time and entering college the next year. The range of IQ's included in the sample to the left of the cutoff is indicated by the row headings; the range to the right is indicated by the column heading. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level.

Appendix Table A6. Impacts of Gifted Education of Graduating On-Time and Entering College with Various Bandwidths

A. Boys

Bandwidth on Left	Bandwidth on Right: 3	4	5	6	7	8	9	10	11	12
3	0.817 (0.463)	0.766 (0.429)	0.665 (0.396)	0.549 (0.344)	0.494 (0.335)	0.447 (0.304)	0.425 (0.311)	0.427 (0.314)	0.444 (0.319)	0.451 (0.317)
4	0.788 (0.374)	0.735 (0.336)	0.629 (0.303)	0.512 (0.257)	0.454 (0.249)	0.408 (0.222)	0.384 (0.225)	0.386 (0.229)	0.403 (0.234)	0.410 (0.231)
5	0.714 (0.267)	0.667 (0.226)	0.572 (0.207)	0.470 (0.172)	0.418 (0.166)	0.378 (0.147)	0.355 (0.147)	0.357 (0.153)	0.373 (0.155)	0.379 (0.153)
6	0.645 (0.243)	0.600 (0.205)	0.506 (0.187)	0.410 (0.156)	0.358 (0.151)	0.322 (0.135)	0.298 (0.134)	0.300 (0.139)	0.315 (0.139)	0.321 (0.137)
7	0.641 (0.226)	0.597 (0.192)	0.505 (0.168)	0.410 (0.137)	0.359 (0.132)	0.324 (0.116)	0.300 (0.117)	0.302 (0.121)	0.317 (0.121)	0.323 (0.118)
8	0.578 (0.202)	0.536 (0.176)	0.446 (0.150)	0.357 (0.122)	0.307 (0.117)	0.276 (0.103)	0.252 (0.103)	0.254 (0.105)	0.267 (0.105)	0.273 (0.101)
9	0.505 (0.191)	0.464 (0.167)	0.374 (0.145)	0.292 (0.118)	0.242 (0.112)	0.214 (0.097)	0.189 (0.098)	0.191 (0.099)	0.203 (0.099)	0.210 (0.095)
10	0.495 (0.184)	0.454 (0.159)	0.364 (0.135)	0.283 (0.107)	0.233 (0.100)	0.206 (0.087)	0.181 (0.087)	0.183 (0.089)	0.195 (0.089)	0.201 (0.084)
11	0.471 (0.178)	0.431 (0.152)	0.343 (0.127)	0.264 (0.101)	0.215 (0.097)	0.189 (0.084)	0.164 (0.085)	0.166 (0.087)	0.178 (0.086)	0.184 (0.081)
12	0.448 (0.170)	0.408 (0.144)	0.321 (0.119)	0.244 (0.095)	0.195 (0.089)	0.171 (0.077)	0.146 (0.078)	0.148 (0.080)	0.159 (0.078)	0.165 (0.073)
13	0.407 (0.162)	0.369 (0.138)	0.282 (0.113)	0.210 (0.090)	0.161 (0.083)	0.140 (0.073)	0.114 (0.074)	0.116 (0.074)	0.127 (0.072)	0.133 (0.067)
14	0.381 (0.159)	0.343 (0.136)	0.259 (0.113)	0.189 (0.089)	0.141 (0.082)	0.121 (0.072)	0.095 (0.073)	0.097 (0.073)	0.108 (0.071)	0.114 (0.066)

Notes: This table presents estimates from local linear regression discontinuity specifications of the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. The dependent variable in all specifications is the event of completing high school on time and entering college the next year. The range of IQ's included in the sample to the left of the cutoff is indicated by the row headings; the range to the right is indicated by the column heading. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level.

B. Girls

Bandwidth on Left	Bandwidth on Right: 3	4	5	6	7	8	9	10	11	12
3	0.064	0.086	0.068	0.072	0.061	0.083	0.086	0.091	0.088	0.117
	(0.237)	(0.230)	(0.215)	(0.218)	(0.224)	(0.221)	(0.215)	(0.217)	(0.216)	(0.213)
4	0.049	0.073	0.054	0.058	0.046	0.069	0.072	0.077	0.074	0.104
	(0.178)	(0.162)	(0.155)	(0.154)	(0.158)	(0.154)	(0.148)	(0.148)	(0.148)	(0.147)
5	0.092	0.115	0.095	0.101	0.090	0.113	0.116	0.121	0.118	0.147
	(0.165)	(0.146)	(0.137)	(0.136)	(0.139)	(0.135)	(0.129)	(0.129)	(0.128)	(0.127)
6	0.060	0.084	0.065	0.069	0.057	0.081	0.084	0.089	0.086	0.116
	(0.160)	(0.141)	(0.127)	(0.125)	(0.127)	(0.122)	(0.116)	(0.117)	(0.115)	(0.115)
7	-0.012	0.012	-0.004	-0.003	-0.016	0.006	0.010	0.014	0.011	0.042
	(0.150)	(0.129)	(0.115)	(0.110)	(0.110)	(0.106)	(0.101)	(0.101)	(0.100)	(0.100)
8	0.031	0.055	0.037	0.040	0.028	0.051	0.054	0.058	0.055	0.086
	(0.138)	(0.117)	(0.104)	(0.098)	(0.099)	(0.094)	(0.090)	(0.091)	(0.090)	(0.091)
9	0.016	0.040	0.023	0.025	0.012	0.035	0.039	0.043	0.040	0.071
	(0.135)	(0.114)	(0.101)	(0.095)	(0.096)	(0.090)	(0.085)	(0.085)	(0.084)	(0.085)
10	0.007	0.031	0.014	0.016	0.003	0.026	0.029	0.033	0.030	0.061
	(0.126)	(0.106)	(0.093)	(0.086)	(0.086)	(0.081)	(0.078)	(0.077)	(0.077)	(0.078)
11	0.013	0.037	0.019	0.022	0.009	0.032	0.036	0.040	0.037	0.067
	(0.125)	(0.106)	(0.093)	(0.085)	(0.085)	(0.080)	(0.077)	(0.076)	(0.075)	(0.077)
12	0.009	0.033	0.016	0.019	0.005	0.028	0.032	0.036	0.033	0.064
	(0.124)	(0.103)	(0.091)	(0.083)	(0.083)	(0.077)	(0.074)	(0.073)	(0.072)	(0.074)
13	0.030	0.054	0.036	0.039	0.027	0.049	0.053	0.057	0.054	0.085
	(0.121)	(0.100)	(0.088)	(0.079)	(0.079)	(0.073)	(0.070)	(0.069)	(0.068)	(0.070)
14	0.015	0.039	0.021	0.024	0.011	0.034	0.038	0.042	0.039	0.069
	(0.118)	(0.098)	(0.086)	(0.077)	(0.077)	(0.072)	(0.069)	(0.068)	(0.067)	(0.069)

Notes: This table presents estimates from local linear regression discontinuity specifications of the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. The dependent variable in all specification is the event of completing high school on time and entering college the next year. The range of IQ's included in the sample to the left of the cutoff is indicated by the row headings; the range to the right is indicated by the column heading. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Entries in parentheses are standard errors, clustered at the school level.

Appendix Table A7. Mean Squared Errors of Local Linear Models with Various Symmetric Bandwidths

	(1)	(2)	(3)	(4)
	Boys		Girls	
Bandwidth	RMSE	p>F	RMSE	p>F
4	0.479	0.747	0.449	0.886
5	0.480	0.712	0.445	0.957
6	0.481	0.691	0.445	0.986
7	0.481	0.672	0.446	0.910
8	0.482	0.738	0.446	0.839
9	0.482	0.540	0.448	0.914
10	0.483	0.685	0.449	0.960
11	0.484	0.770	0.449	0.983
12	0.485	0.833	0.452	0.866
13	0.486	0.790	0.452	0.850
14	0.486	0.784	0.453	0.843
15	0.486	0.784	0.453	0.843

Notes: This table compares the performance of local linear models with symmetric bandwidths that vary between 4 and 15 IQ points. Columns 1 and 3 report the root mean squared error of the local linear regression corresponding to each bandwidth. Columns 2 and 4 report the *p*-values from *F*-tests comparing the linear model to the unrestricted alternative with a dummy for each value of IQ.

Appendix Table A8. Alternative Measures of Graduation and College Enrollment Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Grad HS On-time (Full Sample)	Grad HS On-time (Cohorts 2003-2011)	Grad HS (On-time or following year)	Grad HS On-time + Enrolled Within 1 Year	Grad HS + Enrolled Within 1 Year	Grad HS On-time + Enrolled Within 2 Years
Panel A. Boys Only						
BW 8	0.08	0.07	0.05	0.30**	0.31**	0.30*
	(0.08)	(0.09)	(0.08)	(0.12)	(0.12)	(0.11)
Obs.	1,879	1,598	1,598	1,598	1,598	1,598
BW 6	0.19	0.16	0.11	0.41*	0.40*	0.36*
	(0.12)	(0.14)	(0.12)	(0.17)	(0.17)	(0.17)
Obs.	1,451	1,242	1,242	1,242	1,242	1,242
BW 10	0.05	0.04	0.04	0.18+	0.19+	0.17+
	(0.07)	(0.08)	(0.07)	(0.10)	(0.10)	(0.10)
Obs.	2,336	1,974	1,974	1,974	1,974	1,974
Panel B. Girls Only						
BW 8	0.02	0.01	0.01	0.06	0.05	0.06
	(0.05)	(0.05)	(0.05)	(0.10)	(0.10)	(0.09)
Obs.	1,647	1,420	1,420	1,420	1,420	1,420
BW 6	-0.00	-0.02	-0.02	0.03	0.03	0.08
	(0.05)	(0.06)	(0.06)	(0.13)	(0.13)	(0.12)
Obs.	1,294	1,123	1,123	1,123	1,123	1,123
BW 10	0.02	-0.00	-0.02	0.04	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.08)	(0.08)	(0.08)
Obs.	2,048	1,757	1,757	1,757	1,757	1,757

Notes: This table presents estimates from local linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. Column 1 reports results for all cohorts (2003-2012) in our analysis, while Columns 2-6 report results excluding the 2012 cohort for whom our data includes only one year beyond their "on-time" graduation year. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix Table A9. Regression Discontinuity Effects for College SAT Outcomes

	(1)	(2)
	Has SAT Score	SAT Score
Panel A. Boys Only		
BW 8	-0.09	19.29
	(0.11)	(43.31)
Obs.	1,879	1,291
BW 6	-0.15	-20.91
	(0.16)	(59.54)
Obs.	1,451	1,003
BW 10	-0.15	10.99
	(0.09)	(38.17)
Obs.	2,336	1,583
Panel B. Girls Only		
BW 8	0.01	-11.09
	(0.10)	(32.00)
Obs.	1,647	1,266
BW 6	-0.07	-10.38
	(0.12)	(42.11)
Obs.	1,294	1,006
BW 10	0.02	0.31
	(0.08)	(27.50)
Obs.	2,048	1,569

Notes: This table presents estimates from local linear regression discontinuity specifications. The bandwidths are IQ scores in the range 106-124 (BW 8), 108-122 (BW 6), and 104-126 (BW 10). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having an IQ score ≥ 116 as an instrument. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). The column label at the top indicates the dependent variable in each specification. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). Standard errors are clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix Table A10. Regression Discontinuity Effects and Multiple Hypothesis Testing

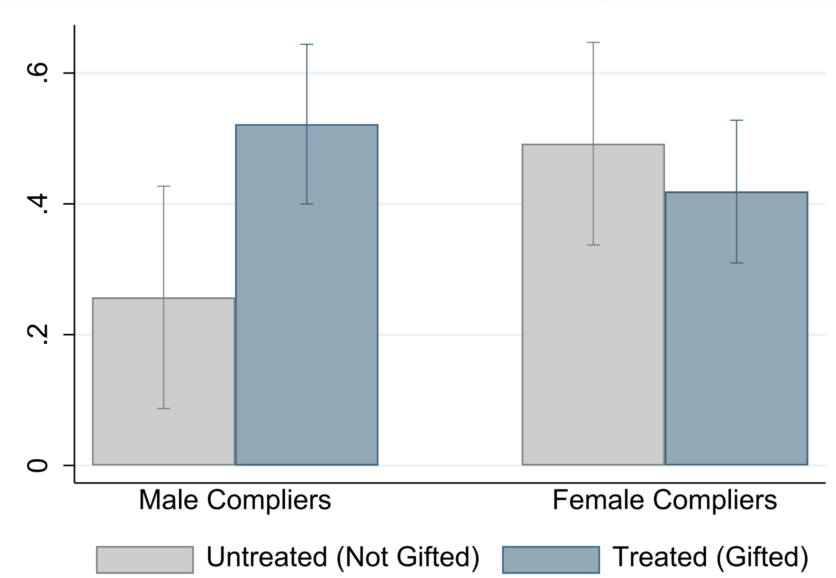
	Effect on Boys	Per Comparison *p*-value	Adjusted *q*-value	Effect on Girls	Per Comparison *p*-value	Adjusted *q*-value
	(1)	(2)	(3)	(4)	(5)	(6)
A. Non-Cognitive Outcomes						
Gifted/High-Achieving Classroom Enrollment	0.72**	< 0.001	0.001	0.49***	< 0.001	0.001
GEM Enrollment, 6th Grade	0.26*	0.011	0.027	-0.07	0.447	0.906
G6-G8 Peers, Math Courses (σ units)	0.35**	< 0.001	0.007	0.04	0.686	0.906
G6-G8 Peers, Reading Courses (σ units)	0.48**	< 0.001	0.001	0.23***	< 0.001	0.048
Algebra Enrollment, by 8th Grade	0.30**	< 0.001	0.012	-0.04	0.715	0.906
G6-G8, No Suspensions	0.10	0.276	0.477	0.00	0.958	0.963
HS Peers, Math Courses (σ units)	0.25*	0.037	0.079	-0.02	0.840	0.939
HS Peers, Reading Courses (σ units)	0.35*	< 0.001	0.01	0.07	0.428	0.906
HS Math GPA	0.37+	0.066	0.126	-0.13	0.393	0.906
HS Lang. Arts GPA	0.11	0.564	0.825	0.01	0.963	0.963
HS GPA	0.01	0.934	0.949	-0.11	0.266	0.906
Number of AP Courses	2.47**	0.005	0.016	0.26	0.770	0.915
B. Cognitive Outcomes						
G6-G8 Test Scores (σ units)	0.04	0.814	0.949	-0.17	0.152	0.722
G6-G8 Math Test Scores (σ units)	-0.01	0.949	0.949	-0.09	0.489	0.906
G6-G8 Reading Test Scores (σ units)	0.05	0.761	0.949	-0.21	0.134	0.722
PSAT (Percentile)	0.45	0.938	0.949	-2.09	0.624	0.906
PSAT Math (Percentile)	0.60	0.919	0.949	-4.06	0.363	0.906
PSAT Reading (Percentile)	3.63	0.555	0.825	-2.79	0.565	0.906
C. College						
Grad HS On Time + Enroll Within 1 Yr.	0.28**	0.008	0.022	0.05	0.592	0.906

Notes: This table presents estimates from linear regression discontinuity specifications. The bandwidth is the set of IQ scores in the range 106-124. Columns 1 and 4 reports 2SLS estimates for the effect of being identified as gifted using an indicator for having IQ ≥ 116 as an instrument, samples of Plan B boys and girls, respectively. All estimated models exclude IQ scores that fall in the "donut" region (i.e., scores 114-116). We report standard (unadjusted) *p*-values in Columns 2 and 5. Statistical significance based on these *p*-values is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$ in Columns 1 and 4. To address concerns about multiple hypothesis testing, we use a two-step procedure from Benjamini, Krieger, and Yekutieli (2006) to calculate adjusted "*q*-values" that control for the false discovery rate (FDR), which is the proportion of rejections that are false positives (Type I errors). The adjusted *q*-values are reported in Columns 3 and 6.

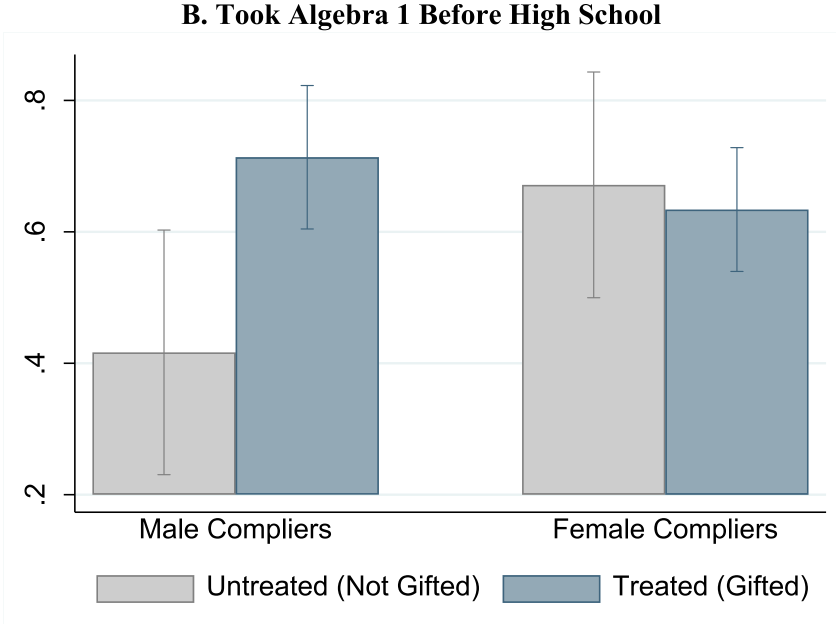
Appendix B: Mean Potential Outcomes for Complier Boys and Girls, with and without Gifted Status

Figure B1. Middle School Math Course Enrollment

A. Took Accelerated Math Track ("GEM") in 6th Grade



B. Took Algebra 1 Before High School

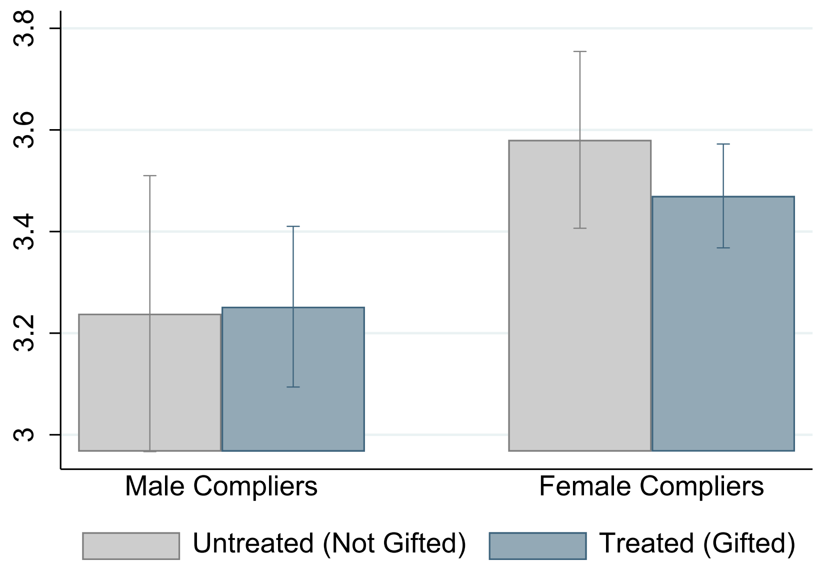


Notes: This figure shows mean potential outcomes for the complying boys (left side) and complying girls (right side) in our sample with and without assignment to gifted status. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.)

Figure B2. High School GPA's

A. High School GPA – Math Courses

B. High School GPA – Overall

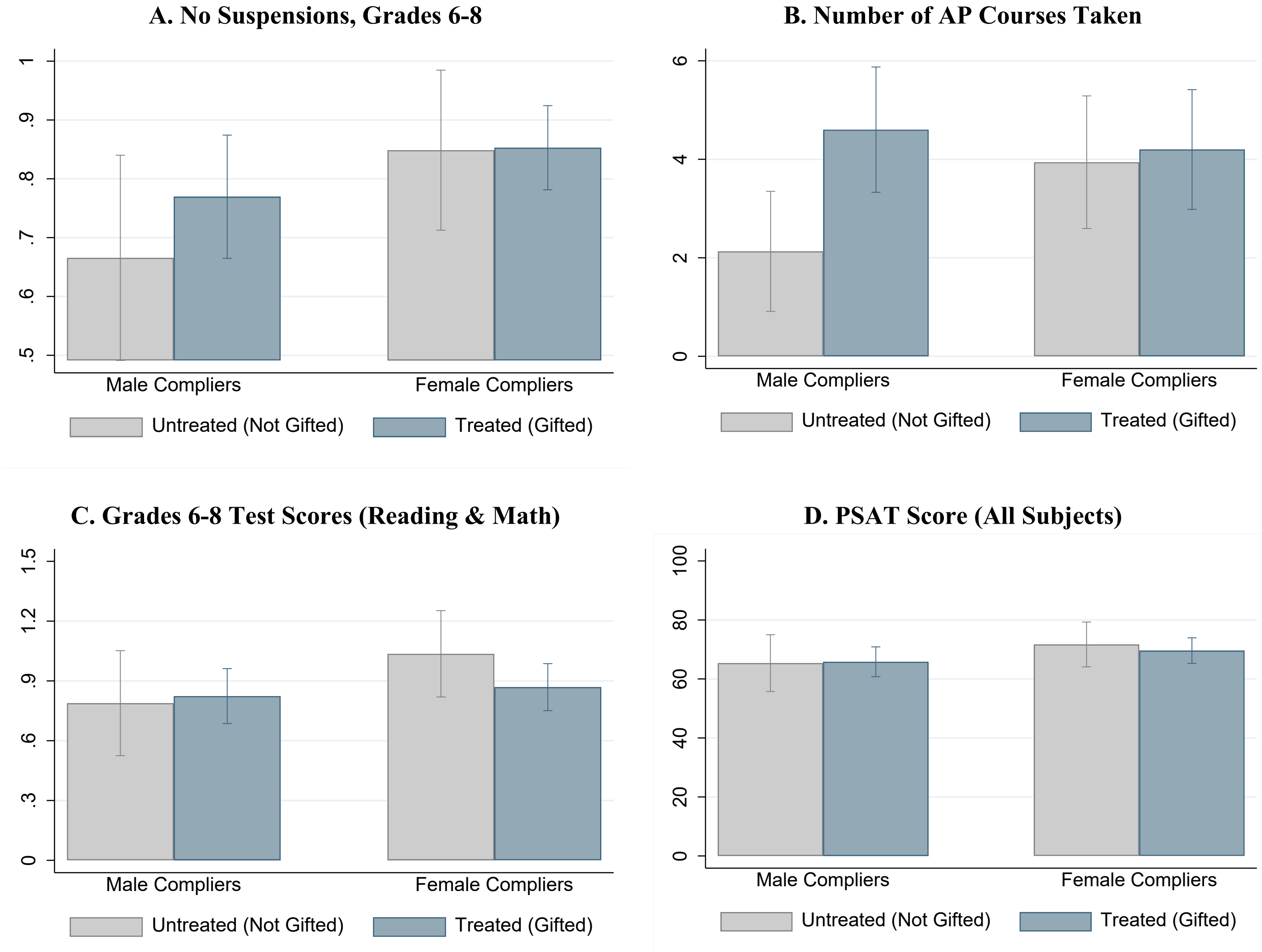


Notes: This figure shows mean potential outcomes for the complying boys (left side) and complying girls (right side) in our sample with and without assignment to gifted status. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.)

Figure B3. Survey Response on Guidance with Selecting Challenging Courses

Notes: This figure shows mean potential outcomes for the complying boys (left side) and complying girls (right side) with and without assignment to gifted status. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.) The outcome is the survey response of 6th graders, collected on a 5-point Likert scale measuring agreement (from 1 = strongly disagree to 5 = strongly agree) with the statement: "This year, school staff helped me to select high level courses that challenge my abilities." The student questionnaire was only collected in the 2008-2011 5th-grade cohorts, so this analysis is based only on students in these four cohorts who had non-missing responses.

Figure B4. Additional Intermediate Outcomes

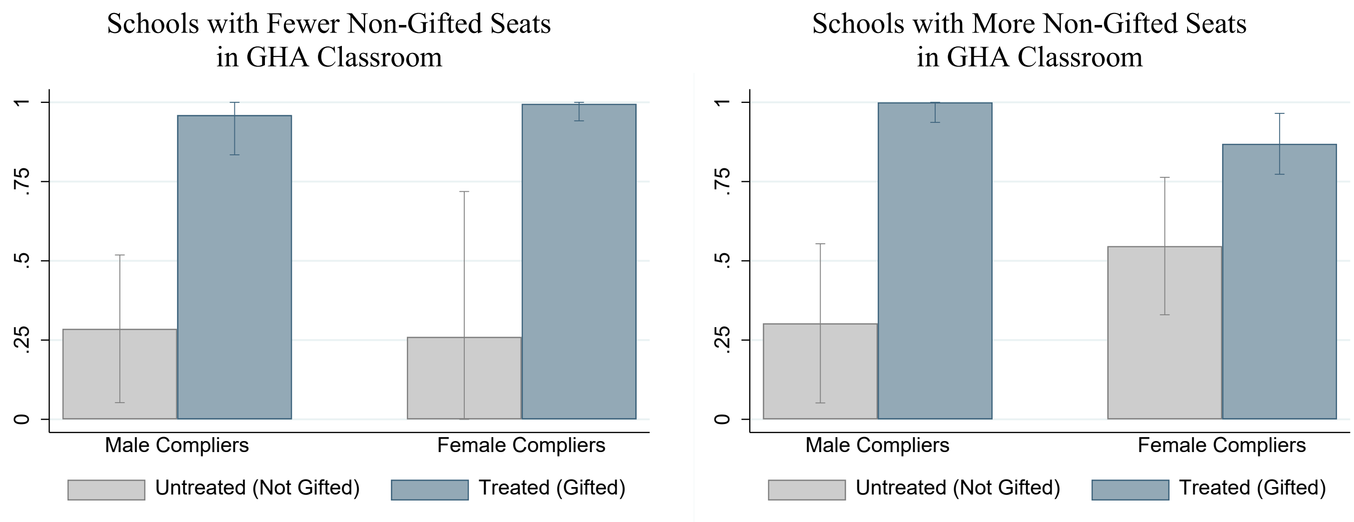


Notes: This figure shows mean potential outcomes for the complying boys (left side) and complying girls (right side) in our sample with and without assignment to gifted status. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.)

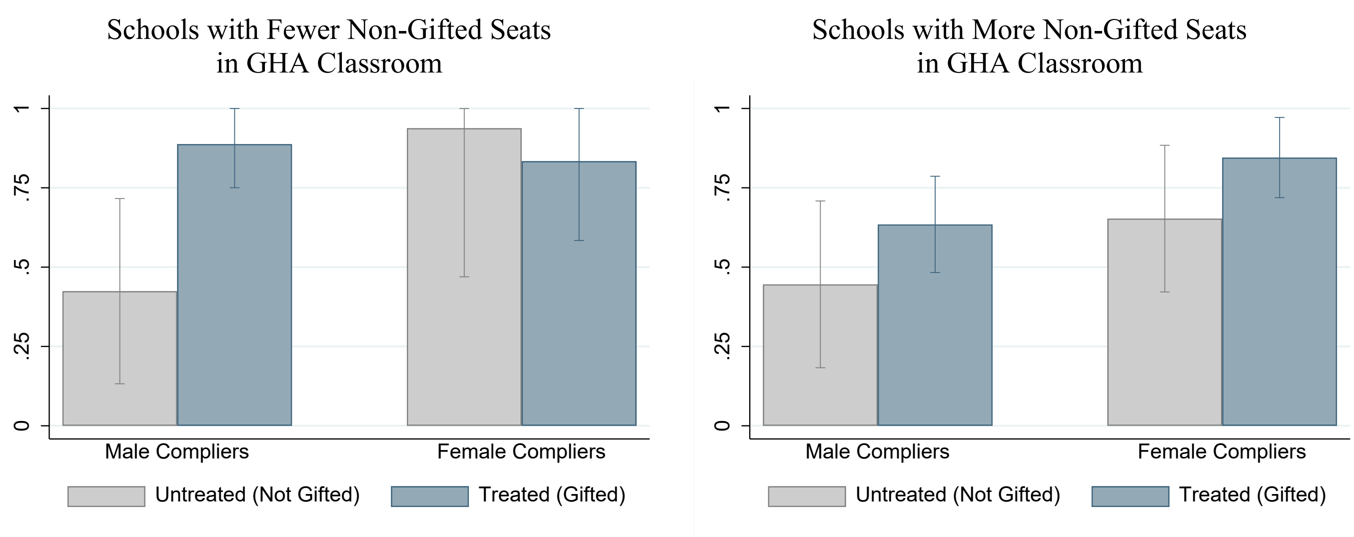
Appendix C: Analysis of Impacts of Gifted and High Achieving (GHA) Classrooms

Appendix Figure C1: Role of Participation in Gifted/High Achiever Classroom

A. GHA Participation



B. On-Time College Enrollment



Notes: This figure shows mean potential outcomes for the complying boys (left side) and complying girls (right side) in our sample with and without assignment to gifted status. The estimates are constructed by applying the approach of Abadie (2002) to local linear RD IV specifications using a symmetric bandwidth of 8 (i.e., IQ scores between 106-124) and excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). (See notes to Figure 6 for details.) Panels on left use students enrolled in schools where >30% of GHA classroom seats were typically filled by gifted students; the student-weighed mean share of non-gifted students in these classrooms was around 50%. Panels on the right use schools where <30% of GHA scats were filled by gifted students; the student-weighed mean share of non-gifted students in these classrooms was more than 80%.

Appendix Table C1. Role of Participation in Gifted/High Achiever Classroom

	(1)	(2)	(3)	(4)	(5)	(6)
	GHA Classroom Participation			On-Time College Enrollment		
	Pooled	Fewer Non-Gifted Seats in GHA Classroom	More Non-Gifted Seats in GHA Classroom	Pooled	Fewer Non-Gifted Seats in GHA Classroom	More Non-Gifted Seats in GHA Classroom
Panel A. Boys Only						
BW 8	0.68**	0.67**	0.71**	0.31**	0.46**	0.19
	(0.10)	(0.14)	(0.14)	(0.12)	(0.17)	(0.15)
Obs.	1,403	499	904	1,403	499	904
Panel B. Girls Only						
BW 8	0.45**	0.74**	0.32*	0.10	-0.10	0.19
	(0.12)	(0.24)	(0.13)	(0.12)	(0.25)	(0.13)
Obs.	1,240	428	812	1,240	428	812

Notes: This table presents estimates from local linear regression discontinuity models for the effects of gifted status on GHA classroom participation (columns 1-3) and on-time college enrollment (columns 4-6). All columns show 2SLS estimates for the effect of being identified as gifted using an indicator for having IQ ≥ 116 as an instrument. All estimated models are estimated using a symmetric 8-point bandwidth (i.e., IQ scores in the range 106-124), excluding IQ scores that fall in the "donut" region (i.e., scores 114-116). The samples in columns (1) and (4) include all boys (Panel A) or girls (Panel B) for whom we have information on their school's 4th-grade GHA classroom. This excludes the first three cohorts of our main analysis sample (those in 5th grade in 2003-2005) and a small number of students who were not enrolled in the District in 4th grade or who attended a school without a GHA classroom. Columns (2) and (5) use students enrolled in schools where >30% of GHA classroom seats were typically filled by gifted students; the student-weighed mean share of non-gifted students in these classrooms was around 50%. Columns (3) and (6) use schools where <30% of GHA seats were filled by gifted students; the student-weighed mean share of non-gifted students in these classrooms is more than 80%. Standard errors are clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Appendix Table C2. Rank-Based RD Estimates for Effects of GHA Classroom Participation for Non-Gifted, FRL/ELL High Achievers

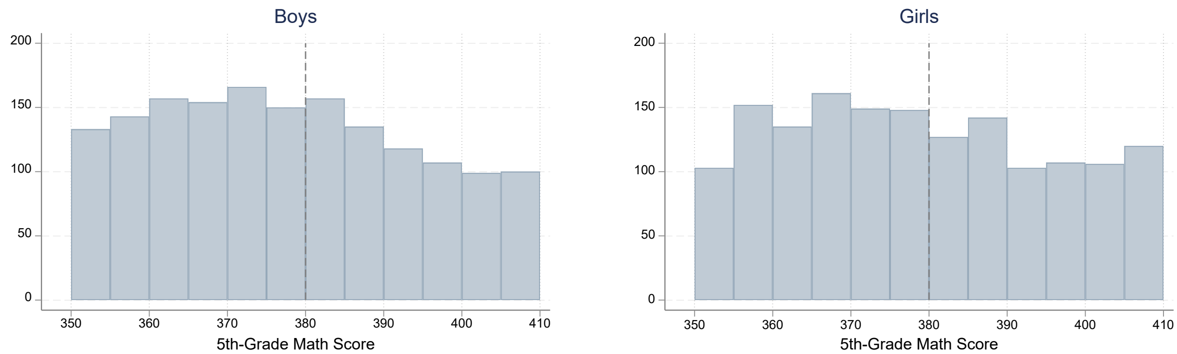
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	First Stage	Reduced-Form		2SLS						
	In G4 GHA Classroom	G3 Test Scores	G3 Enjoys Learning	GEM in G6	Algebra by G8	Peer Qual. G6-G8	No Susp. G6-G8	Test Scores G6-G8	Math Scores G6-G8	Reading Scores G6-G8
Panel A. Boys Only										
BW 10 (Rank Distance)	0.20**	-0.08	0.04	0.54+	0.52+	0.30	0.68+	0.51	0.75+	0.18
	(0.06)	(0.05)	(0.07)	(0.30)	(0.27)	(0.23)	(0.38)	(0.37)	(0.43)	(0.41)
Obs.	896	896	809	896	896	896	896	894	892	891
Panel B. Girls Only										
BW 10 (Rank Distance)	0.28**	-0.02	0.01	0.09	-0.21	0.09	0.18	0.44+	0.40	0.44
	(0.06)	(0.05)	(0.07)	(0.17)	(0.14)	(0.16)	(0.19)	(0.25)	(0.28)	(0.28)
Obs.	981	981	883	981	981	981	981	975	971	974

Notes: This table presents an analysis of the effects of fourth-grade GHA participation using an alternative research design and sample based on Card and Giuliano (2016b). The running variable in the design is a student's within-school/cohort rank on an index of third-grade test scores which school officials used to determine eligibility among non-gifted children to fill any seats not taken by gifted students. Participation in GHA for non-gifted "high achievers" is instrumented using school/cohort-specific thresholds. For comparability with the Plan B gifted analysis sample, we focus on boys and girls who were eligible for the Free/Reduced Price Lunch program and English Language Learners. Of the original Card and Giuliano (2016b) analysis sample of N=4,144, there are 985 boys and 1,069 girls (2,054 children total) who meet these Plan B criteria. When we restrict the sample further to children who are observed through grade 8 with complete information on all non-cognitive outcomes in grades 6-8, we are left with a sample of 896 boys and 981 girls. All results are from linear regression discontinuity specifications. The bandwidths for the linear specifications are a student's test score rank being within 10 points of a school-specific threshold for GHA enrollment. The column label at the top indicates the dependent variable in each specification. Standard errors are clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

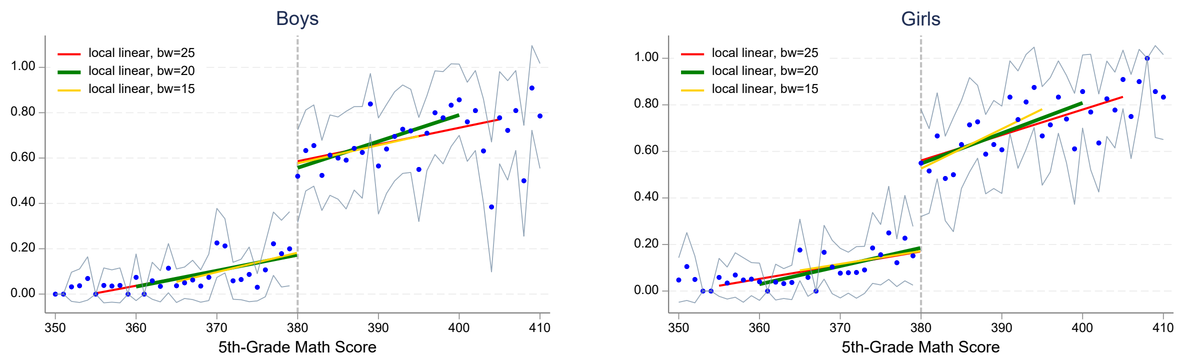
Appendix D: Regression Discontinuity Analysis of Impacts of Middle School Math Acceleration (GEM)

Appendix Figure D1: Running Variable Distribution and First-Stage Relationships

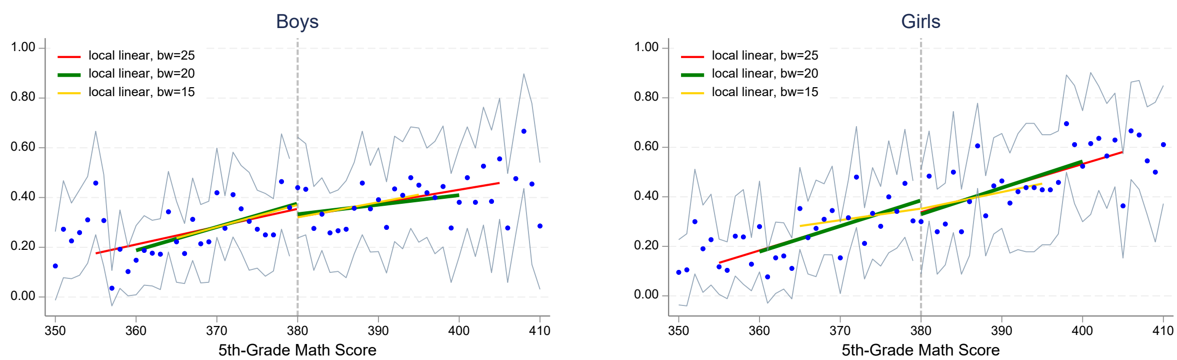
A. Histogram of Running Variable (5th Grade Standardized Math Score)



B. Participated in Accelerated Middle School Math Program (GEM) in 6th Grade

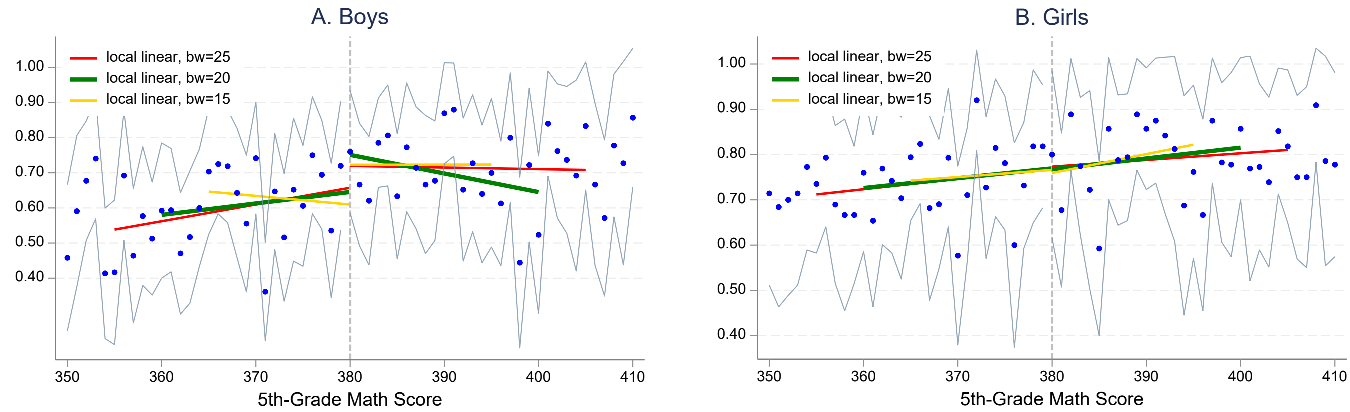


C. Identified as Gifted by 5th Grade



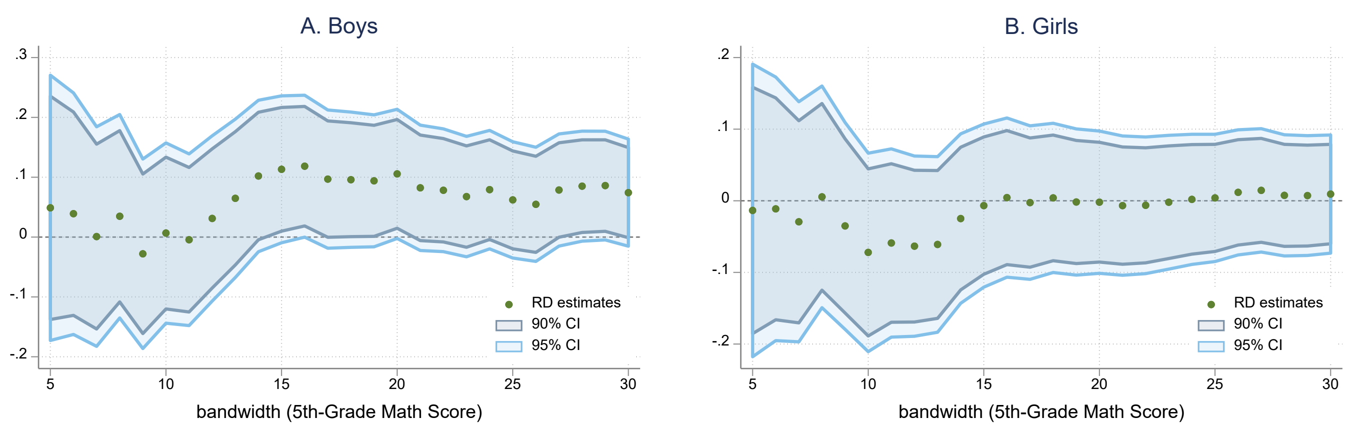
Notes: Panel A shows histograms of the student 5th-grade math score that serves as the running variable in our RD models for the effects of GEM participation. The samples include boys (left column) and girls (right column) from our IQ-based RD analysis sample whose 5th-grade math score was within +/-30 points of the GEM eligibility threshold of 380. We exclude the final cohort (i.e., those who completed 5th grade in 2012) due to a change in the scale of state-wide achievement scores in 2012. Panel B shows the first-stage relationship for GEM participation (for which district policy creates a discontinuity at the threshold score of 380), while Panel C shows an analogous plot for gifted identification (which is not expected to vary discontinuously at the GEM eligibility threshold). Panels B and C show means at each test-score value (blue dots) for students within +/-30 points of the threshold, along with 95% confidence intervals for the mean values (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 25 (red), 20 (green), or 15 (yellow).

Appendix Figure D2: Reduced-Form Relationship for Impact of GEM Eligibility on On-Time Graduation and College Entry



Notes: These figures illustrate the reduced-form relationships for boys (Panel A) and girls (Panel B) between the fraction of students who graduate high school on time and enter college and their scores on the 5th-grade math test used to determine eligibility for GEM. As in Figure D1, the samples includes boys and girls from our IQ-based RD analysis sample whose score was within +/-30 points of the GEM eligibility threshold of 380. The figures plot means (blue dots) at each test score value along with 95% confidence intervals for the mean values (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 25 (red), 20 (green), or 15 (yellow).

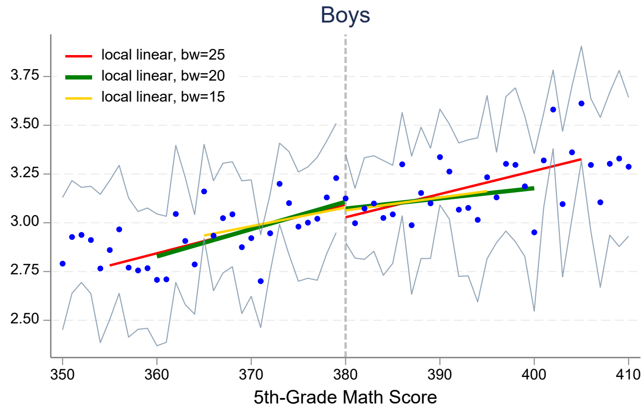
Appendix Figure D3: Reduced-Form Estimates for Impacts of GEM Eligibility on College Entry, Local Linear Models with Varying Bandwidths



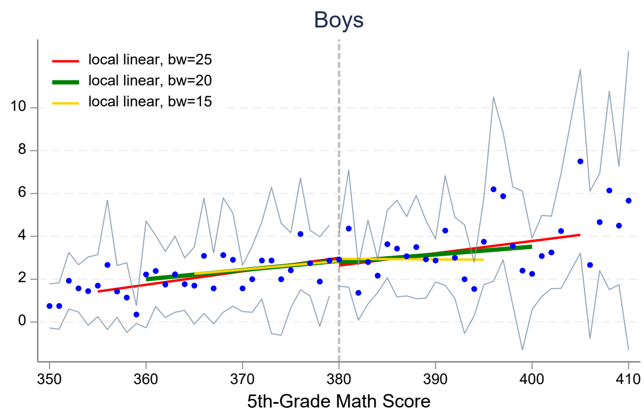
Notes: This figure plots reduced-form discontinuity estimates from local linear RD models with varying symmetric bandwidths to the left and right of the GEM eligibility threshold, separately for boys (Panel A) and girls (Panel B). The running variable is the student's score on the end-of-year standardized math test in 5th grade, and the dependent variable is an indicator for graduating from high school on time and enrolling in college the following year. The samples include all boys and girls from our IQ-based RD analysis sample whose 5th-grade math score was within +/-30 points of the GEM eligibility threshold of 380 – with the exception of the final cohort (i.e., those who completed 5th grade in 2012), who we exclude due to a change in the scale of state-wide achievement scores in 2012.

Appendix Figure D4: Impacts of Math Acceleration on High School Grades and AP Courses

A. High School GPA – Math Courses



B. Number of AP Courses



Notes: These figures illustrate the reduced-form relationships for boys (left) and girls (right) between the dependent variable (indicated by the subhead for each panel) and scores on the 5th-grade math test used to determine eligibility for GEM. As in Figure D1, the samples includes boys and girls from our IQ-based RD analysis sample whose score was within +/-30 points of the GEM eligibility threshold of 380. The figures plot means (blue dots) at each test score value along with 95% confidence intervals for the mean values (thin blue lines) and fitted values from local linear RD models with symmetric bandwidths of 25 (red), 20 (green), or 15 (yellow).

Table D1. Regression Discontinuity Effects of GEM for On-time Graduation and College Enrollment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline (Pre-gifted) Measures				First-Stage	Reduced Form	2SLS
	Grade 2, average *z*-score (Math and Reading)	Grade 3, average *z*-score (Math and Reading)	Predicted On-time Enrollment	Identified as Gifted	GEM Enrollment, 6th Grade	Grad HS On time + Enrolled Within 1 Year	Grad HS On time + Enrolled Within 1 Year
Panel A. Boys Only							
BW 20	-0.08	-0.04	0.00	-0.04	0.38**	0.11*	0.28+
	(0.09)	(0.07)	(0.02)	(0.06)	(0.05)	(0.05)	(0.14)
Obs.	935	1,135	1,165	1,165	1,165	1,165	1,165
BW 15	-0.05	0.07	0.01	-0.05	0.39**	0.11+	0.29+
	(0.11)	(0.07)	(0.02)	(0.06)	(0.06)	(0.07)	(0.17)
Obs.	718	875	900	900	900	900	900
BW 25	-0.08	-0.02	0.00	-0.03	0.42**	0.06	0.15
	(0.08)	(0.06)	(0.01)	(0.05)	(0.04)	(0.05)	(0.12)
Obs.	1,121	1,363	1,404	1,404	1,404	1,404	1,404
Panel B. Girls Only							
BW 20	0.01	-0.06	-0.02+	-0.06	0.36**	-0.00	-0.01
	(0.09)	(0.06)	(0.01)	(0.05)	(0.06)	(0.04)	(0.12)
Obs.	872	1,070	1,093	1,093	1,093	1,093	1,093
BW 15	0.06	-0.03	-0.01	-0.00	0.35**	-0.01	-0.02
	(0.11)	(0.06)	(0.01)	(0.07)	(0.07)	(0.05)	(0.14)
Obs.	681	835	851	851	851	851	851
BW 25	-0.02	-0.05	-0.02*	-0.04	0.39**	0.00	0.03
	(0.07)	(0.05)	(0.01)	(0.05)	(0.05)	(0.04)	(0.11)
Obs.	1,080	1,321	1,352	1,352	1,352	1,352	1,352

Notes: This table presents estimates from linear regression discontinuity specifications. The bandwidths for the linear specifications are 5^{th}-grade math test scores in the range 360-400 (BW 20), 365-395 (BW 15), and 355-405 (BW 25). The column label at the top indicates the dependent variable in each specification. In columns 1-6, the entries are coefficients on an indicator for having a 5^{th}-grade standardized math score ≥ 380. Column 7 shows 2SLS estimates for the effect of GEM enrollment in 6^{th} grade, using an indicator for 5^{th}-grade math score ≥ 380 is an instrument. Standard errors are clustered at the school level. Statistical significance is denoted by: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Appendix Table D2. Comparison of Plan B Gifted and GEM Compliers

	(1)	(2)
	Plan B, Gifted, IQ Scores 106-124	
	Plan B, Complier Boys	GEM RD, Complier Boys
Student Characteristics		
White	0.12	0.23
	(0.16)	(0.06)
Black	0.67	0.32
	(0.24)	(0.07)
Hispanic	0.17	0.35
	(0.21)	(0.07)
FRL	0.61	0.86
	(0.18)	(0.06)
ELL	0.14	0.06
	(0.09)	(0.03)
G2 Avg. Test *z*-score	0.08	0.66
	(0.54)	(0.12)
G2 Avg. Math Test z-score	0.59	0.71
	(0.46)	(0.13)
G2 Avg. Reading Test z-score	-0.35	0.6
	(0.74)	(0.15)
G3, Avg. Test *z*-score	0.77	0.83
	(0.24)	(0.09)
G3, Avg. Math *z*-score	0.78	0.86
	(0.27)	(0.09)
G3, Avg. Reading *z*-score	0.73	0.79
	(0.29)	(0.12)
G3, Enjoy Learning at School	4.29	4.40
(Survey, 1=lowest to 5=highest)	(0.11)	(0.23)
Student's School Characteristics		
Share Black	0.39	0.40
	(0.11)	(0.04)
Share Hispanic	0.26	0.25
	(0.05)	(0.02)
Share FRL	0.62	0.56
	(0.11)	(0.04)
Median HH Income	45.84	53.89
	(7.90)	(2.41)
Avg. Test *z*-score	-0.08	-0.04
	(0.13)	(0.05)

Notes: This table presents estimates of the mean characteristics of compliers with the treatment defined as being enrolled in the GEM program in grade 6. Column 1 shows characteristics of the male compliers in our design for disadvantaged gifted students. These compliers were induced to participate in GEM because their IQ scores just met the gifted threshold of 116. Column 2 shows characteristics of the male compliers in the GEM eligibility RD design used in Section VI.b. These compliers were induced to participate in GEM because their 5th-grade math test scores just met the GEM eligibility threshold for all students (including non-gifted). Complier means are estimated by applying the approach of Abadie (2002).