Is Gifted Education a Bright Idea?
Assessing the Impact of Gifted and Talented Programs on Achievement and Behavior

Sa Bui[1]

Steven G. Craig

Scott Imberman

Department of Economics
University of Houston

Abstract

In this paper we determine how the receipt of receiving gifted and talented (GT) services affects student outcomes. We identify the causal relationship through a regression discontinuity on eligibility guidelines, and find that for students on the margin of elgibility there is no discernable impact. While the peers of marginal GT students improves, grades are found to fall by over 2 points, leading us to suspect invidious comparison to explain lack of achievement. We then examine lottery outcomes for two magnet schools, and find that despite the wider variety of initial student quality that there are no measurable achievement impacts.

April, 2011

[1] Department of Economics, 204 McElhinney Hall, Houston, TX 77204-5019. Correspondence should be made to Imberman at simberman@uh.edu or Craig at scraig@uh.edu. We would like to thank Aimee Chin, Brian Kovak, Jacob Vigdor and seminar participants at APPAM, University of Maryland and Carnegie Mellon University.

I. Introduction

Gifted education has received renewed interest due to the pending reauthorization of the No Child Left Behind Act (NCLB), in part because some research has shown that NCLB may have diverted resources from programs such as gifted and talented (GT) programs for high achieving students (Neal and Schanzenbach, 2010; Rebeck, 2008). The opportunity costs of such resources are difficult to discern, however, because little is known about the effectiveness of GT programs for the three million US GT students that receive these services. GT programs might be effective because either they result in the grouping of students by ability, or because they offer a variety of specialized resources, including specially trained teachers and a more advanced curriculum. While early research found that ability grouping was helpful, many of these studies were likely biased due to unobserved characteristics of students, such as motivation, that simultaneously lead students to be successful and to be grouped in high ability classrooms.[2] Recently, some researchers have tried to address the bias issue in ability grouping, but with mixed results over a range of students (Argys, Rees and Brewer, 1996; Betts and Shkolnik, 2000; Epple, Newlon and Romano, 2002; Figlio and Page, 2002; and Duflo, Dupas and Kremer, forthcoming). Our work here significantly expands the research scope for understanding gifted and talented programs, as we explicitly address the overall effectiveness of GT programs with two unique strategies for overcoming the potential bias issues. One strategy is a regression discontinuity on the student eligibility border, the other is an analysis of a GT lottery for magnet students.

Specifically, all fifth grade students in a particular large urban school district in the

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[2] See Kulik and Kulik (1997) for a review.

Southwest (LUSD-SW) have been evaluated since 2007 to determine eligibility for gifted and talented services starting in 6th grade. Eligibility is identified by a set of well-defined cutoffs on an index score that is based on achievement tests, a non-verbal ability test, grades, teacher recommendations, and socio-economic status. We exploit these cutoff scores to set up a regression discontinuity (RD) design whereby students who score just above the cutoffs are compared to those who score just below. Under certain conditions, for which we provide evidence that this analysis meets, our estimates can be interpreted as the causal impact of enrolling in a gifted and talented program on achievement and behavior. The RD design only evaluates students at the border of eligibility, thus our estimates are of a local average treatment effect (LATE). This research design allows us to ascertain the effectiveness of GT programs conditional on how the minimum criteria for eligibility is set.

The second research strategy that we employ covers the entire range of student ability (as measured by the school district), but for a small sample. Specifically, two of the middle schools with magnet GT programs in this school district are over-subscribed. They fill their magnet slots for students, therefore, by randomly conducting a lottery among students who are eligible for GT services. This allows us to examine achievement differences between students that win the lottery and attend the magnet GT schools, and those who lose the lottery and attend neighborhood schools with GT services. These estimates, therefore, are of the advantage of a magnet GT program that is pervasive throughout the school compared to a localized program inserted as part of a neighborhood school.

To our knowledge, only Bhatt (2009) specifically studies the effect of GT programs on student outcomes, although Davis, Engberg, Epple, Sieg and Zimmer (2010) find that higher income parents are more likely to stay in public schools when their children are eligible for GT programs. While Bhatt finds significant improvements in math achievement, her instrumental variables (IV) methodology suffers from weak instruments, leaving open the potential that her estimates are biased. Our work offers a somewhat wider scope of inquiry, and further offers the two distinct identification strategies. Thus, our study will be the first to establish credibly causal estimates of the impacts GT programs on student achievement.

The results from our RD analysis, which is a LATE on marginally GT students, is that students exposed to GT curriculum for the entirety of 6th grade plus half of 7th grade are found to exhibit no significant improvement in achievement. This is despite substantial increases in average peer achievement, the likelihood of being placed in advanced classes, and the likelihood of attending a GT magnet program, and teacher quality in the magnet programs. This is also the case for most subgroups, although we find evidence of improvements in language for Hispanic students. The lottery results for the two magnet middle schools also show little improvement in overall 7th grade achievement, although we generally find that science scores improve relative to students who attend their neighborhood GT program. In our large urban school district (LUSD), the RD population corresponds to students for whom the inter-quartile ranges for achievement are between the 69th and 89th percentiles in reading and the 81st and 94th percentiles in math.[3] The lottery results suggests the full range of students is more likely to show positive effects of the GT program, although these effects seem to be concentrated in science, and not in reading, language, math, or social studies.

There are several pathways through which exposure to a GT curriculum might increase

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[3] Based on Stanford Achievement Test scores for students within 10 distance units (described in more detail below) of the eligibility cutoff.

achievement. One path is the teacher herself. GT teachers receive additional voluntary training compared to regular program teachers, and thus may be more motivated by higher achieving students in addition to any beneficial effects of the training. Additionally, principals may assign GT classes to teachers who are more effective at generating learning regardless of their credentials. Further, pertinent to the lottery test, magnet schools for GT programs may offer a more attractive environment for teachers interested in gifted students, and thus they may have the opportunity to attract the most effective teachers for this group.

GT program participation could also affect students through peer effects. Students in a GT classroom will spend that time in the company of other gifted students, and will thus be exposed to higher achieving peers. For a marginal GT student, however, the peer effect may not necessarily be positive. That is, a marginal GT student is likely to go from being near the top of the regular class to being near the bottom of the GT class. If peer effects follow a monotonic model whereby being surrounded by higher achieving students improves one's own achievement as found in Imberman, Kugler and Sacerdote (2010), then this should be helpful. On the other hand the invidious comparison model, proposed by Hoxby and Weingarth (2006), suggests students may be demoralized from going from the top of the regular student distribution to the bottom of the GT student distribution. We present suggestive evidence using course grades that indicates that invidious comparison may be one important component.

A third pathway is that the GT curriculum itself may be helpful, either because it is more effective by being targeted, or more stimulating.[4] Again for marginal GT students, however, a more

[4] Conversations with school district officials suggests that the curriculum is more likely to include more detail, rather than cover the regular curriculum more quickly.

advanced curriculum may or may not be helpful depending on the appropriateness of the qualification threshold. A fourth pathway is that being declared GT may induce parents to take a more active role in their children's education. Finally, GT identification could open up access to different schools through magnet programs. These schools could be of higher quality than others and they could generate a better student-school match due to the increase in schooling options for the student. Our results here do not address all of these mechanisms, but nonetheless allow a broader view at some of them in the context of our overall findings. Specifically, the RD addresses the LATE for the marginal student, and depending on the school district's objective no overall effect may be optimal for the district. Showing that the LATE balances higher achieving peers with lower grades and lower attendance suggests, without firmly identifying, how some of the mechanisms trade-off.

The lottery effects are also interesting in this context, as they work on a different margin. Specifically, the lottery results evaluate the relative effect of magnet GT schools compared to GT programs in neighborhood schools. We demonstrate that there are significant quality differences between magnet and neighborhood schools in teachers as well as peers, although some argue that there are no curricular differences. Unfortunately, we are not able to say whether the small scope of observable achievement differences is because the advantages in teachers and peers is offset by invidious comparison or material that is too advanced, or whether standardized achievement tests are not the appropriate measurement tool.

II. The Gifted and Talented Program in LUSD

LUSD is a very large school district in the Southwestern US with over 200,000 students. In general, the district is heavily minority and very low income as is the case with most inner-city districts in the US, although the minority population is more heavily Hispanic rather than African-American. Table 1 shows that gifted students in LUSD are less likely to be on free or reduced price lunch than other students, are more likely to be white, are less likely to have limited English proficiency, and perform better on both cognitive and non-cognitive measures of output. Schools in LUSD also have a potential incentive for attracting gifted students as LUSD provides a funding boost of 12% over the average daily allotment for a regular student.[5]

In order to be identified as GT in LUSD, a student must meet the eligibility criteria set forth in the "gifted and talented identification matrix," which we will refer to as "the matrix." A copy of the matrix for 2009-10 is provided in Figure 1. The matrix converts scores on standardized tests – Stanford Achievement Test for English speaking students, the Aprenda exam for some Spanish speaking students with limited English proficiency – scores on the Naglieri non-verbal abilities test (NNAT), average course grades, teacher recommendations, and indicators for socio-economic status into an index score we call "total matrix points."[6]

There are two pathways by which students can meet the threshold for GT classification using the matrix scores. First, they can be identified if they have 56 total matrix points, including at least 16 points from the Stanford Achievement test and 10 points from the NNAT.[7] Alternatively, students

[5] This could be offset by the extra wages that GT certified teachers receive.

[6] For socioeconomic status, students get 5 extra points (out of 100) for having limited English proficiency, being classified as special education or being classified as economically disadvantaged. Students who are members of a minority group get a further 3 point bonus.

[7] Students can reach 16 points from the Stanford Achievement Tests using a variety of different test scores across subjects in different combinations. For example a student who is in the 90th

can qualify by having 62 total matrix points. During 5th grade all students are evaluated for GT, including those who participated in the GT program elementary school.[8] This selection framework allows us to model qualification along the eligibility boundary by using a fuzzy RD methodology.[9] Specifically, while all students who meet the requirements above qualify, not all end up being classified as GT because parents are allowed to opt-out of the program, or students may enroll and then withdraw. Further, some who do not initially meet the requirements later become identified as GT. This is mainly because either parents appeal the recorded matrix scores by submitting an alternative standardized test provided it was taken within the prior 12 months, or because missing data is added later or corrected.[10]

Table 1 also shows the sample means from the lottery sample in the right hand columns. As can be seen in Box B, the students in the lottery are significantly stronger than the students in the RD sample, consistent with our view that the lottery students span the spectrum of GT students while the RD sample is of the "marginal" GT students. For example, the lottery students average about 0.7 standard deviations higher than the marginal GT students on the standardized tests, and also average fewer disciplinary infractions and have higher attendance. The demographic

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percentile in math and the 80th percentile in reading will qualify regardless of science and social studies scores. Alternatively a student could meet this requirement by scoring in the 80th percentile in all four exams. See Figure 1 for details on the score to points conversions. For the Naglieri test a score of 104 (no percentiles are given) would be equivalent to 10 matrix points.

[8] All students are also evaluated for GT services in kindergarten, but unfortunately the matrix data was incomplete prohibiting us from evaluating the GT program in elementary school.

[9] One reason for a 'fuzzy' specification is because there seem to be a few exceptions to the matrix points. Students who qualify for GT in middle or high school generally keep their status through graduation, although they can be removed from the GT program if they perform poorly.

[10] Later we provide evidence that the missing data does not appear to substantially influence our results.

characteristics of the lottery students also vary from the RD sample. The key element we primarily take from the lottery sample, however, is the selective attrition rate. That is, of the 542 students that entered the lottery, 18.8% are not in the school district by 7th grade (and in fact, most attrit in 6th). This is actually a lower rate than in the RD sample, where 25.5% of the students evaluated in 5th grade exit by 7th grade. It is not a random sample, however, because Table 1 also shows that lottery losers are generally of higher achievement than others. As we are unable to follow students who do not remain in LUSD, we weight our lottery regressions to mimic the original sample of students that enter the lottery. While much smaller than the RD sample, the lottery sample allows us to examine the potential returns to the magnet GT schools over the entire range of student quality.

III. Model and Specification

1. GT Program Evaluation Using RD Analysis

The objective of the RD analysis is to estimate a LATE which will differentiate students who enroll into the GT program from students who do not, but who are otherwise equivalent. Figure 2 shows the increase in GT identification one and two years after evaluation (6th and 7th grade, respectively) as students' matrix points increase. The gradual increase up to 28% at the first cutoff (of students with a matrix score of 56) reflects missing data as well as the District's appeals process. Upon reaching the first threshold GT enrollment jumps to around 45%. Enrollment increases further at a steep rate between the two cutoffs, hitting 79% at the second cutoff (62 matrix points). After reaching the second cutoff at 62 points, GT enrollment slightly increases further to 82%.

Given that the increase in GT over this range, while steep, is not discontinuous, we convert the two thresholds into a single cutoff.[11] To do this we map the matrix scores into three-dimensional space as shown in Figure 3. Each axis reflects one of the three portions of the matrix score that determines eligibility – NNAT points, Stanford points, and other points. Students who are on or above the surface are eligible for GT while those below or behind are ineligible. We then take the Euclidean distance from each student's total matrix points to the nearest integer combination on the surface.[12] The resulting value, which we call the distance to the qualification threshold, equals zero if the student just barely qualifies for GT. Figure 4 shows GT enrollment as a function of distance from the GT Euclidean threshold. Students just below the cutoff have about a 25% likelihood of being in GT, however students just above the threshold have a likelihood of approximately 79%.

Since qualification for GT via the observed matrix score does not translate perfectly with enrollment in GT due appeals, substitute exams, and data issues, our estimation strategy uses a "fuzzy RD" model where we conduct a two-stage least squares regression within a range of values that includes the cutoff (Hahn, Todd and Van der Klaauw, 2001; Lee and Lemieux, 2009). For most of this paper we will use ten matrix points below and above the cutoff for our bandwidth since the relationship between distance and gifted status is close to linear over this range, allowing us to use a linear smoother. Nonetheless, we will show later that our results are not sensitive to the choice of bandwidth or smoother. Hence, we estimate the following two-stage least squares (2SLS) model:

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[11] We thank Jake Vigdor for this idea.

[12] The Euclidean distance is measured as $Distance_i = \sqrt{(Stanford_i - Stanford_s)^2 + (NNAT_i - NNAT_s)^2 + (Other_i - Other_s)^2}$ where *i* refers to the student's own score and *s* refers to the closest integer combination on the surface. We thank Jake Vigdor for first suggesting this method to us.

$$\textbf{(1)}\ GT_{i,t+k} = \delta + \gamma Above_{it} + \rho_1 Distance_{it} + \rho_2 Distance_{it} \times Above_{it} + \Omega X_i + \mu_{i,t+k}$$

$$\textbf{(2)}\ Y_{i,t+k} = \alpha + \beta GT_{i,t+k} + \lambda_1 Distance_{it} + \lambda_2 Distance_{it} \times Above_{it} + \Phi X_i + \epsilon_{i,t+k}$$

where $Above_{it}$ is an indicator for whether student *i* in year *t* has a distance measure above the cutoff, *Distance* is the Euclidean distance of the student's matrix score to the eligibility cutoff, and *X* is a set of pre-existing (5th grade) observable characteristics which includes the 5th grade dependent variable (e.g. lagged achievement), gender, ethnicity, gifted status, and LEP status. *GT* is an indicator for whether the student is enrolled in a GT program in year $t + k$ and *Y* is a test score, attendance, or disciplinary infractions in that year. Since students are tested in January of each year, we focus on scores in the second year after evaluation (7th grade) as assessment in the first year will only provide five months of program exposure, although we also provide estimates for 6th grade.

2. GT Magnet Evaluation Using School Lotteries

LUSD has two GT middle school magnet programs which are over-subscribed, and as a result the district uses lotteries to allocate the available spaces.[13] Specifically, GT eligible students who do not reside in the school attendance zones are allowed to apply to one magnet school. While the losers of the lottery will still have the opportunity to receive GT services in their neighborhood

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[13] There are 8 GT magnet middle schools in total (out of 38 middle schools), but only two are over-subscribed. By seventh grade, of the 109 lottery losers, 13 end up in one of the lottery magnet schools, and 8 in the other, while only 5 attend one of the other six GT magnet programs. On the other hand, of the 265 lottery winners, 3 attend one of the other six GT magnets by 7th grade.

school, the two magnet schools are considered to be premium schools because of the large proportion of GT students. Table 1 suggests that lottery winners appear to be of higher ability (as measured by 5th grade test scores) than lottery losers. As discussed above, however, this pattern is a result of attrition by the highest quality students, which we confirm below econometrically. Thus our analysis compares the performance of students who win the lottery and attend one of the two magnet GT programs to those who lose the lottery and either attend a neighborhood GT program in the District, or a magnet school based on a different specialty.

Despite the important differences in the sample of students studied, and in alternative treatments, our results from both samples are similar. We find in the RD that marginal GT students do not out-perform their colleagues that do not receive GT services. We find in the lottery sample that magnet GT students out-perform their GT colleagues only in science, but not in any of the other four subject areas. This is despite that we demonstrate that the GT or magnet students associate with better peers, and seem to receive stronger teachers. One suggestive piece of evidence is that course grades are found to be considerably lower statistically and quantitatively in both samples for students in the 'preferred' treatment.

IV. Data

Our data consists of the administrative records of LUSD from 2007-08 to 2009-10. While we have data for universal assessments conducted in 2006-07, many schools were given exemptions from the new rules that year in order to allow for an orderly transition to the new system. Hence the discontinuities in that year are too small to generate precise estimates. Thus, we limit our RD sample by starting in 2007-08, the second year of the mandatory GT assessment, and examine outcomes through the 2009-10 school year. For outcomes we use scale scores standardized across

LUSD within grade and year on the Stanford Achievement Test, and as well we examine attendance and extreme discipline (suspensions or worse). The Stanford Achievement results are in standard deviation units for each of math, reading, language, science and social studies. After restricting the sample to a 20 unit band around the cutoff, we look at achievement of approximately 2,600 students in 7th grade for one year and 5,500 students in 6th grade over two years who were evaluated for GT in 5th grade. We also have the number of disciplinary infractions resulting in an in-school suspension or more severe punishment and attendance rates for 2008-09 and earlier, allowing us to consider non-cognitive outputs for the first year of the sample.

1. Tests of Validity of RD Design

A primary concern with any regression-discontinuity analysis is that there is a potential for manipulation of the forcing variable (qualification for GT) that determines treatment. Such manipulation could bias the results if the manipulation is correlated with the results of treatment (Lee and Lemieux, 2009). We find, however, that the differences in density around the discontinuity are similar in size to changes at other parts of the distribution, suggesting that manipulation is unlikely to be occurring.[14]

Second, tests reported in Table 2 find no discernable difference in the likelihood of a student having any of the observed characteristics based on GT status except for prior math scores. The first seven columns report that the demographic characteristics of students do not respond to GT status.

[14] Ideally one would like to conduct McCrary's (2008) test. However, by construction the distance measure has an empty mass between 0 and 1 and -1 and 0 since the smallest distance to another integer point is 1. Since there is positive mass between integers further out, this could mistakenly generate a positive result. Hence, instead we test for discontinuities at the two cutoffs in the total matrix points to check for manipulation. In both cases the test is statistically insignificant.

The next five columns show that GT students are less likely to have high math scores, although the point estimate is quite small.[15] The next two columns show that GT status is not correlated with discipline, nor is it correlated with attendance. Column (15) shows missing matrix data has no discontinuity at the GT boundary. The next two columns address the most likely source of manipulation, which is teacher evaluation.[16] We find no statistically significant discontinuity in either measure of teacher recommendation, the score (col 16) or the resulting matrix points (col 17). Later, we will provide an additional specification test to further check for bias from teacher manipulation through their recommendations. Finally, in columns (18) though (20) we test whether there is a discontinuous likelihood of being enrolled 2 years after evaluation. Given that Davis, et al. (2010) find evidence that high income students are more likely to stay in public schools if identified as GT, we check if such a phenomenon occurs in LUSD. We find no statistically significant change in the likelihood of enrollment at the discontinuity regardless of the student's economic status.

Given these results we see little evidence that GT qualifications were manipulated in a way that would violate the assumptions underlying the RD methodology. Because of the statistically significant, although small, effect of prior math scores, we control for prior test scores from 5th grade in the analysis below.

2. Tests of Validity of Lottery Design

[15] Tests using the 6th grade sample were similar for all measures except for females which show a small but statistically significant increase.

[16] Although teacher recommendations are due before the achievement scores are calculated, district officials informed us that this is a soft deadline and many teachers submitted their recommendations late.

Table 8 presents the balancing tests for the lottery sample. If the lottery is random there should be no significant results, while if the lottery is conducted to achieve a certain outcome based on observable characteristics of students those effects should be evident. The Table 8 results strongly suggest that the lotteries for both magnet middle schools are conducted in a random way, as the only significant coefficient is that on math scores for the *ex-post* sample. As we have discussed elsewhere, this is most likely an effect of the attrition from the sample. We therefore take two steps. As with the RD analysis, we add controls for lagged student scores as well as demographics to the outcome regressions. Second, we use a weighting procedure in the regressions so mimic the original lottery sample.

V. Results

The RD analysis on students that are just above the GT qualification line is based on the Euclidean distance to the boundary, based on the two alternative qualification paths (total matrix points, or standardized tests alone). The fuzzy RD analysis uses GT matrix points as an IV for actual GT status, based on the earlier discussion showing that the GT qualification line does not exactly predict GT status, despite the sharp discontinuity at the qualification line. The RD analysis includes a linear smoothing function, although the results are not sensitive to the functional form.

Effect of GT Classification on Achievement and Behavior

Figure 5 presents the initial 2SLS results for three of the five achievement tests, and Figure 6 for the other two. These achievement test results are from 7^{th} grade, thus encompassing about a year and a half of GT exposure. The comparison is between students of up to ten points above the

GT qualification boundary with students a similar distance below. As a result, the LATE RD results compare GT exposure for students that are marginally qualified for admittance into the GT program. Figure 5 shows that there is no improvement in reading or language Stanford scores, and that there is a negative point estimate for math. This coefficient is shown in Panel A of Table 3 to be significant at the 5% level, indicating that marginal students admitted into the GT programs receive lower scores on their Stanford math achievement tests than students of otherwise similar ability but who were not exposed to the GT program. Figure 6 confirms the findings in the other columns of Table 3, which is that there are no discernable impacts on achievement tests in social studies or science. Panel B of Table 3 indicates that when lagged achievement test scores as well as student characteristics are added as control variables that the negative effect on math scores becomes insignificant, despite that we found no discontinuities in student characteristics.

The one student outcome for which we find consistent effects of participation in the GT program is in attendance. Despite the purportedly more stimulating curriculum which the GT program represents, we find a drop in attendance at the 10% level of statistical significance in the Baseline Panel A results. The addition of individual student controls and lagged test scores does not significantly alter the magnitude or clarity of this result.

The Panel C results presented in the Table take the possibility of teacher manipulation seriously, despite that there was very little statistical evidence of such manipulation. Specifically, for students within 10 points of the boundary before the teacher recommendation, the teacher recommendation is potentially determinative. Thus we run a regression using the entire sample on all student demographic and achievement test characteristics to get a “predicted” teacher recommendation using:

$$(3)\ TotalPoints_i = \alpha + \beta_1 StanfordPoints_i + \beta_2 NNATPoints_i + \beta_3 ObstaclePoints_i + \beta_4 GradePoints_i + \varepsilon_i$$

where *TotalPoints* is the student's final score on the GT qualification matrix, *StanfordPoints* are the number of matrix points received from performance on Stanford Achievement Tests, *NNATPoints* are matrix points from the non-verbal abilities test, *ObstaclePoints* are matrix points from socioeconomic status, and *GradePoints* are matrix points from the student's average grades in 5^{th} grade. The point of this test is to remove the influence of the student's own teacher recommendation from the total matrix score, in case a teacher knows how close a student is to the qualification boundary. The Panel C results show that the only result that is sensitive to this change is that on attendance, where the otherwise negative coefficient we observe becomes positive, although insignificant at conventional levels. This evidence combined with the lack of a discontinuity in teacher scores shown in Table 3 suggests that teacher manipulation of recommendations is not affecting our results.

Impacts of GT on Student Subgroups

To test for heterogeneity in program impacts across student characteristics, Table 4 provides 2SLS estimates for 7^{th} grade for various student populations. In general, we find little evidence of differences by gender, demographics, or economic status. The only distinction is that we find women and Black students who are in the GT program are likely to have lower attendance than their otherwise similar counterparts that are not in a GT program, while for other groups we see no effects on attendance. Thus one possibility is that the weak attendance results in the overall table is because the impact is relevant only for these particular students.

Specification Tests

In Table 5 we test the sensitivity to our RD estimates to model specification. In all models we include the controls from Panel B of Table 4. We find that the lack of finding GT program effects is not generally because of the functional form of the smoother variable, is not because of school fixed effects, nor is it because of the size of the boundary around the GT qualification cutoff line. Further, we use leave-one-out cross validation to identify the optimal bandwidth, and find that our results span these estimates. The exception is that when we use a quadratic smoother as the functional form, we find that participation in a GT program provides about 1/4 of a standard deviation improvement in language achievement scores, and about a .3 standard deviation improvement in science achievement scores. These results become less strong with a cubic smoother, and disappear altogether with other functional forms. The plots in Figures 5 and 6 do not indicate considerable curvature, so we note the possibility of these positive effects, but also note the result is quite fragile as it shows up in none of the other possible specifications.

Lottery Results for GT Magnet Schools

One reason the RD analysis may not show that GT services have positive impact on student outcomes is that the qualification boundary is not selective enough. That is, if the boundary is too low, students who marginally qualify for GT services may not be able to take advantage of the purported benefits, and thus show no difference to the marginal students not taking GT services. Because the RD is a LATE, it is not possible to examine GT effectiveness on other parts of the quality distribution. The lotteries for the two GT magnet middle schools, however, provide us with an alternative window. That is, because the lottery is random over all students who qualify, the comparison is between both strong and less strong students. The disadvantage, however, is that the lottery results will only compare the magnet GT schools to the GT programs in neighborhood schools, or in other magnet schools based on other criteria (non-GT magnets).

The impact on student achievement from winning the lottery and attending one of the two magnet GT middle schools is shown in Table 9. Our preferred specification is the fourth one, which is weighted least squares analysis including controls for lagged test scores and student characteristics. In fact, however, the specification differences are not very important, as all of the results indicate that the magnet GT students perform about .25 of a standard deviation better than students attending other District schools in science. One specification, unweighted but with controls, also shows a positive effect on language for the magnet GT students. The regressions weighted for the original sample, however, show no evidence for such an effect.

Potential Mechanisms

Our analysis is not sufficiently detailed to fully explore the possible mechanisms for finding only extremely modest impacts of GT services. In both of our samples, however, we decisively show that GT students (in the RD sample- see Table 6), and magnet students (in the lottery sample- see Table 10) take their classes with stronger peers than do their otherwise similar students. Given the strength with which peer effects have been found to operate in several different contexts, it might be expected that simply based on peers alone that the GT programs would be found to be effective irrespective of other inputs. Table 6 does show that GT students are more likely to take more challenging courses, although they are not found to be with teachers with larger fixed effects (as measured by equation 3). The lottery student winners, however, are found not only to have stronger peers than their otherwise similar colleagues who lose the lottery, but to have stronger teacher fixed effects as well. It is ironic that the only teacher fixed effect to fail conventional significance tests is in science, where the most robust achievement gains are to be found.

Despite the input gains, however, the positive effects of GT services are found to be very modest. By far the most robust return is in science students among the lottery student winners. None of the marginal GT students are found to out-perform their peers without the benefits of participation in a GT program. One possible mechanism for these findings is in the course grades.

Course grades are not commonly used as research outcomes, since their basis is difficult to compare across institutional environments. That is, teachers may implicitly curve their grades to have identical distributions across a wide variety of students, they may adhere to a school norm that could be very different across schools, or each teacher may construct their own grading algorithm without regard to other grades in a school. On the other hand, the differences in the institutional environment are part of what is being compared by attempting to measure the impact of a GT program. Further, to the extent that grades would conform to a standard and be comparable across schools, it would be more likely to be in a single school district within a specialized curriculum, which is a good description of the GT program. A final point is that irrespective of any lack of validity for the comparison of grades, schools grades are the direct feedback given to students. Grades are explicitly designed to affect student behavior. Thus it might not be surprising if students respond to the grades they receive.

Table 7 presents the results for grades of the students in the RD sample. This table shows that students that qualify for GT services receive statistically significantly lower grades than their otherwise identifical counterparts that do not receive GT services in math and reading, and that these differences are large, about 4 points out of 100 (3 points changes a grade from a B+ to a B, for example). Further, grades in the other 3 subjects also show negative point estimates, and of sufficient magnitude to guess that the lack of precision may be related to sample size.

The results for the lottery sample, shown in Table 10, are even more dramatic. All four subjects show that students in the magnet schools receive statistically significantly lower grades than students in other GT programs. The point estimates range from a minimum of 4 points up to over 8 points in math (out of 100). One possibility for the larger difference in grades among the lottery students compared to the RD students may be because of an implicit minimum grade, in that all GT students are expected to achieve a certain level to maintain their GT status. Irrespective, however, the data is clear that otherwise identical students will receive lower grades in the more rigorous programs. This is not surprising, and is also consistent with the higher achieving peers that we document in both samples.

The impact of peers, however, is not completely clear. Hoxby and Weingarth (2006) propose that peer effects could potentially operate through an invidious comparison (IC) model whereby being surrounded by higher achieving peers is demoralizing, and can reduce achievement. They find some weak evidence that this occurs at the top of the achievement distribution. Imberman, Kugler and Sacerdote (2009) test for IC and find little support for the model. They are only able, however, to identify IC effects at a more aggregate school-wide level, and can only test the model for students below the 75th percentile of achievement. Meanwhile, there is evidence from educational psychology that students who are placed in higher achieving ability groups lose confidence in their ability and exhibit less happiness (Vaille, Heaven and Ciarrochi, 2007; Peterson, Duncan and Canady, 2009; Preckel, Gotz and Frenzel, 2010; Preckel and Brull, 2010). Another somewhat related theory is that the marginal GT students cannot handle the more difficult GT curriculum and hence become demoralized through that mechanism. Thus it is possible that invidious comparison or demoralization of marginal students through the difficulty of the material can play a role in the achievement of gifted students. Whether this effect would be strong enough to counter-balance the other positive effects of GT services requires further examination of all the possible mechanisms determining student performance.

Among the other possible mechanisms which are beyond the reach of our present effort are the ability of the Stanford test to measure outcomes. That is, the Stanford Achievement Test may not distinguish between students at this level since students get almost all of the answers correct. While this may be the case for higher achieving GT students in the lottery sample, it is unlikely for the marginal student in the RD context as they tend to have substantial room for improvement. And in fact, we find larger test gains for the lottery students than the students in the RD sample. Another possibility is that the GT curriculum does not address topics covered in the achievement tests beyond what students learn in a regular class. This is potentially more salient as the GT program focuses more on creative projects and critical thinking rather than an expansion of actual substance covered. Although we cannot rule out this possibility, again it would appear to be more important for the lottery sample than the RD sample.

Another potential explanation for the lack of impact is that GT does not actually generate much of a treatment. For example if students are kept in the same classroom as regular students and perhaps given no more than an extra assignment each week, then the impacts of GT would probably be minimal. Columns (6) through (11) of Table 6 investigate the RD student's course selection. We classify math and English/reading courses into three types – regular, pre-AP (Advanced Placement), and Vanguard – where the latter is a pre-AP course specifically designed for GT students. Students who qualify for GT are much more likely to be enrolled in a Vanguard course than in a standard pre-AP course and are less likely to be enrolled in a regular non-pre-AP math course.[17]

Finally, in columns (15) through (18) of Table 7, and in columns (6) through (9) of Table 10 we investigate whether GT students are assigned to higher quality teachers. To do this we estimate teacher fixed-effects using data on all students in grades 6 through 8 from 2006-07 through 2009-10. Thus we estimate the following model separately for each subject of the Stanford Achievement Test:

(4) $A_{ijt} = \alpha + \gamma A_{ij,t-1} + \Phi X_{ijt} + \lambda_j + \phi_i + \epsilon_{ijt}$

where A is student achievement; $\boldsymbol{X}$ is a set of student level controls including gender, ethnicity, economic disadvantage, LEP, special education, and grade-by-year fixed effects; λ_j is a set of teacher fixed-effects; ϕ_i are student fixed-effects; and ϵ_{ijt} is random error. We estimate this model such that each observation is assigned a weight that reflects the fact that each teacher is only responsible for a portion of the impact on a student proportional to her share of classes in that subject taught to that student. For example if a student takes a class in US history and another class in geography, then the student will have two observations in the social studies regression, one for each class, where he would be given a weight of ½ for each observation. Additionally, since the Stanford exams are given in January, we assign to each student the teachers they had in the spring of the previous academic year and the fall of the current academic year.

After collecting the teacher fixed-effects we match the estimates to student-course combinations for each semester, once again assigning a student-year observation to the courses the student takes in the fall of that year and the spring of the previous year. Finally, we average the

[17] We do not perform this analysis for the GT magnet schools because the entire focus of the magnet schools is theoretically directed at the GT students.

teacher effects for each subject over the students' courses and use those values as the dependent variables in the two tables. The interpretation of the fixed-effect is the marginal impact of a teacher on the average achievement growth in her class, measured in standard deviation units. The results show no significant effects in Table 6, suggesting the marginal GT students are receiving about identical teacher quality as the non GT students. In Table 10, however, we find that the magnet GT students have teachers that are significantly stronger than students that are not enrolled in the GT magnet programs.

VII. Conclusion

In this paper, we identify the impact of providing gifted and talented services on student achievement and behavior. We exploit a unique universal evaluation program in a single school district whereby all students are evaluated for GT eligibility in 5th grade. This allows us to specify an RD for students on either side of the eligibility border, and examine the results achievement differences by 7th grade. We also exploit a second data set, which is that two of the middle schools in this District are over-subcribed, and thus conduct lotteries to determine admission. This second data set allows us a glimpse at a different part of the student ability distribution, as the RD only examines the local average treatment effect around the border.

Our analysis shows that the RD data sample is generally balanced on the observable data we have, conditional on students being near the qualification boundary. The lottery data is also balanced, with the exception that lottery losers that leave the District are more likely to be high achieving. We control for attrition by using weighted least squares. In both data samples, we also present estimates using student characteristics (including lagged exam scores) to control for potential mild deviations.

Both the RD and the lottery results indicate that GT services do not have large impacts on student outcomes. The exception to this statement is that the lottery magnet winners appear to attain higher achievement scores in science. The estimates from these two samples and specifications are reduced forms, in that they do not differentiate among the many mechanisms by which student achievement might be impacted. Our work here is not able to finely differentiate between all of the alternative paths by which a GT program operates on student achievement. Nonetheless, we do find that course grades are lower for the marginal students that enter the GT program. Further, we find that course grades are lower in the highly regarded GT magnet schools. In some sense, the lower grades would seem to be correlated with the higher performing peers. Whether these two effects would always balance in a reduced form sense definitely awaits a more detailed analysis. We can only note that the lack of a positive overall impact is despite the evidence we present of substantial improvements in students' educational environments in both samples. Students who exceed the cutoff score for GT qualification and enroll in a GT program have significantly higher achieving peers, are more likely to be placed in advanced courses, and are more likely to attend GT magnet schools. Students in the GT magnet schools have all of these things, plus we find they are taught by higher quality teachers. We have not completed all of the pieces to the puzzle of understanding GT programs, but have peeled back another layer of the onion.

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Figure 1 - Gifted and Talented Matrix for 2009-10

Gifted and Talented Identification Matrix, K-12
Kindergarten for Spring Services 2009 &
First through Twelfth Grade for the 2009-2010 School Year

STUDENT INFORMATION

Name:______________________ Applying for Grade:______________________

Date of Birth:______________________ ID#______________________ Ethnicity:______________________

Zoned School:______________________ Current School:______________________

First Choice School:______________________ Second Chôice School:______________________

ACHIEVEMENT TEST

Please indicate which test was administered and the administration date. All tests must have been administered within the last 12 months.

☐ **Stanford 9/10** ____________ (Administration Date) ☐ **Aprenda 3** ____________ (Administration Date)

☐ **Other** ______________________ (Name of Test Administered) (Administration Date)

Total Reading NPR

95-99 percentile	12 points
90-94 percentile	10 points
85-89 percentile	8 points
80-84 percentile	6 points
70-79 percentile	4 points

Score:_______ **Points:**_______

Total Math NPR

95-99 percentile	12 points
90-94 percentile	10 points
85-89 percentile	8 points
80-84 percentile	6 points
70-79 percentile	4 points

Score:_______ **Points:**_______

Total Science NPR

95-99 percentile	8 points
90-94 percentile	6 points
85-89 percentile	4 points
80-84 percentile	2 points
70-79 percentile	1 point

Score:_______ **Points:**_______

Total Social Studies NPR

95-99 percentile	8 points
90-94 percentile	6 points
85-89 percentile	4 points
80-84 percentile	2 points
70-79 percentile	1 point

Score:_______ **Points:**_______

Total Environment (Science/Social Studies) NPR (Grades K, 1, 2, 3 only)

95-99 percentile	16 points
90-94 percentile	12 points
85-89 percentile	8 points
80-84 percentile	4 points
70-79 percentile	2 points

Score:_______ **Points:**_______

ABILITY TEST

Naglieri Nonverbal Abilities Test-2
(NNAT-2)
(current year's score)

NAI 124-160	30 points
NAI 119-123	25 points
NAI 113-118	20 points
NAI 108-112	15 points
NAI 104-107	10 points
NAI 100-103	5 points

Score:_______ **Points:**_______

REPORT CARD

95-100%	20 points
90-94%	15 points
85-89%	10 points
80-84%	5 points

Report Card points are calculated using the 4 core subject areas of English/Language Arts, Math, Science, and Social Studies. Please refer to the G/T Report Card Evaluation Rubric on the back of this page for further information.

Matrix Score:_________ **Points:**_______

TEACHER RECOMMENDATION

Score: 90-100	10 points
Score: 80-89	8 points
Score: 70-79	6 points
Score: 60-69	4 points

Teacher Recommendation score calculated using G/T Identification Matrix on page 2.

Score:_______ **Points:**_______

TOTAL MATRIX POINTS

TOTAL MATRIX SCORE:_________

A Matrix that totals 62 points or above is required to be District Qualified for the Vanguard G/T program.

Students can qualify with a Total Matrix Score that totals 56 – 61points if the total points earned for the Stanford/Aprenda equals 16 and the total points earned for the NNAT-2 equals 10.

(Circle one)

District Qualified **Not Qualified**

OBSTACLES

Check all appropriate boxes:
☐ Limited English Proficient
☐ Special Education/504
☐ Low SES
(One or more = 5 points) **Points:**_____

If Low SES Above + Minority(Hispanic or African American) = 3 additional points

Total Points:_______

ADMISSIONS COMMITTEE

Meeting Date:_____________ Date Information Sent to Parents:__________

Committee Members:______________________
Campus G/T Coordinator – completed G/T Identification Matrix

____
G/T Committee Member – verified scores and points

____
VG Neighborhood Principal/Designee or VG Magnet Advanced Academics Dept.

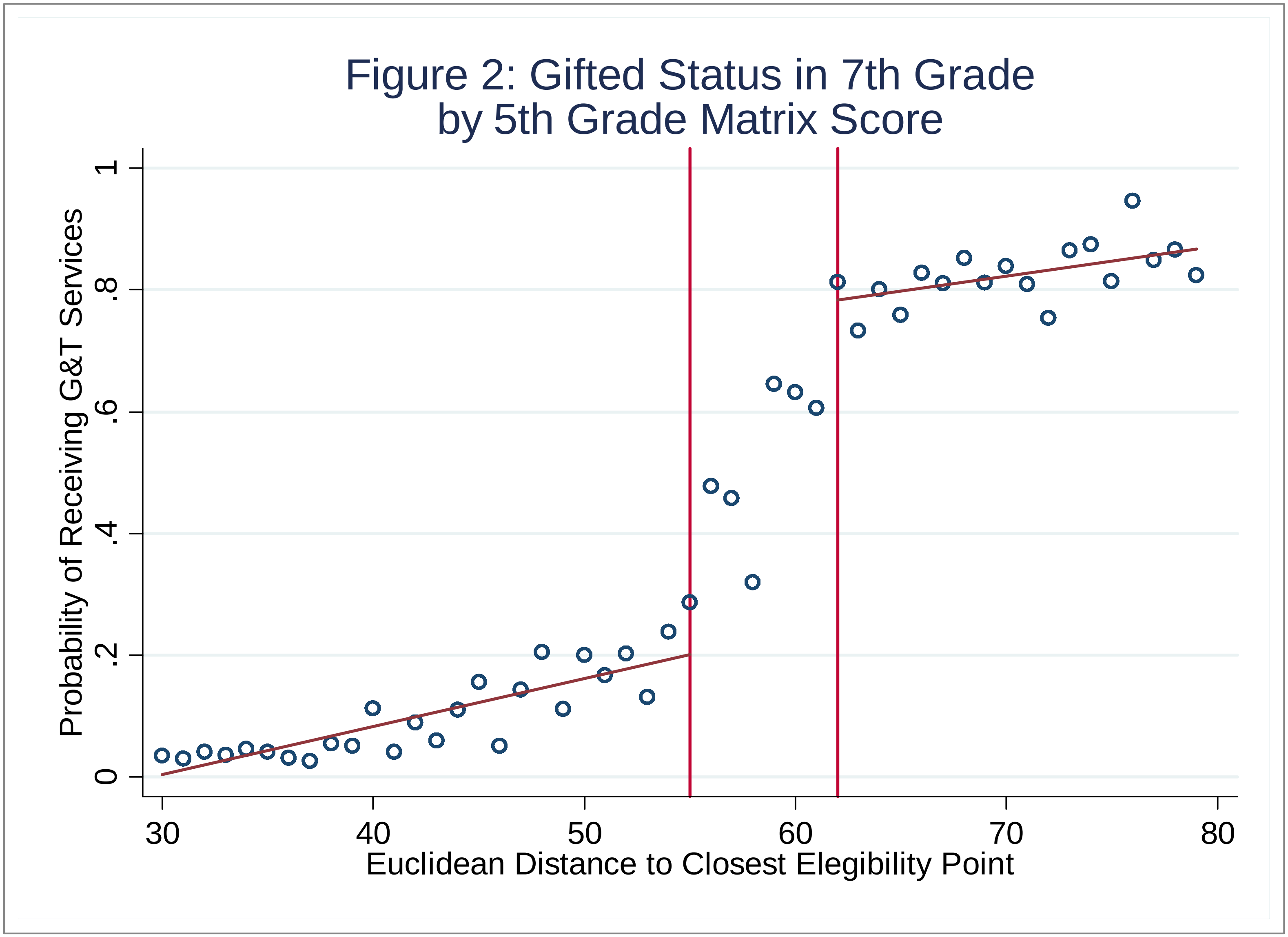
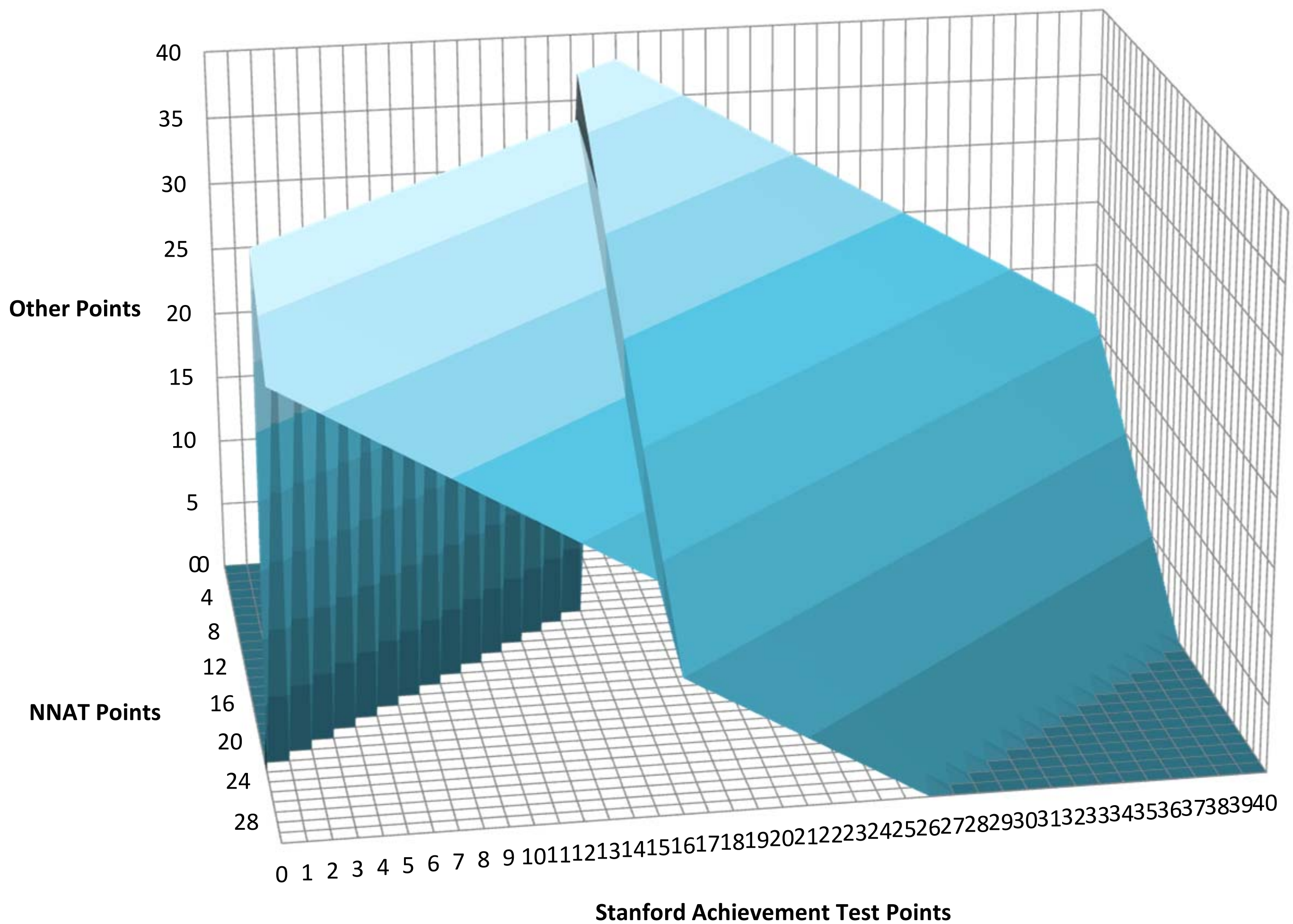


Figure 2: Gifted Status in 7th Grade
by 5th Grade Matrix Score
Probability of Receiving G&T Services
0
.2
.4
.6
.8
1
30
40
50
60
70
80
Euclidean Distance to Closest Elegibility Point

Figure 3: Surface Plot of GT Qualification by Matrix Points



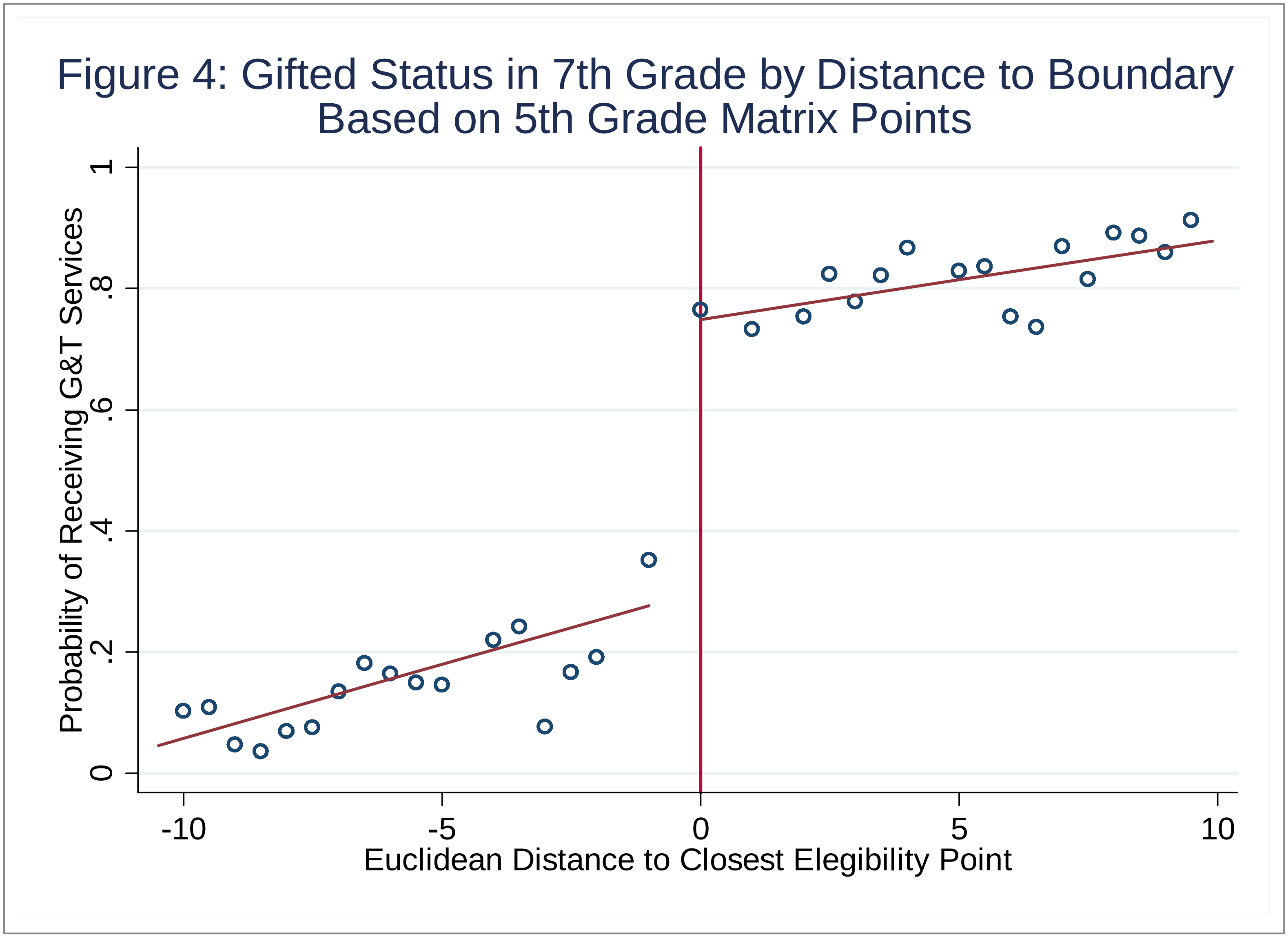


Figure 4: Gifted Status in 7th Grade by Distance to Boundary
Based on 5th Grade Matrix Points
Probability of Receiving G&T Services
0
.2
.4
.6
.8
1
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point

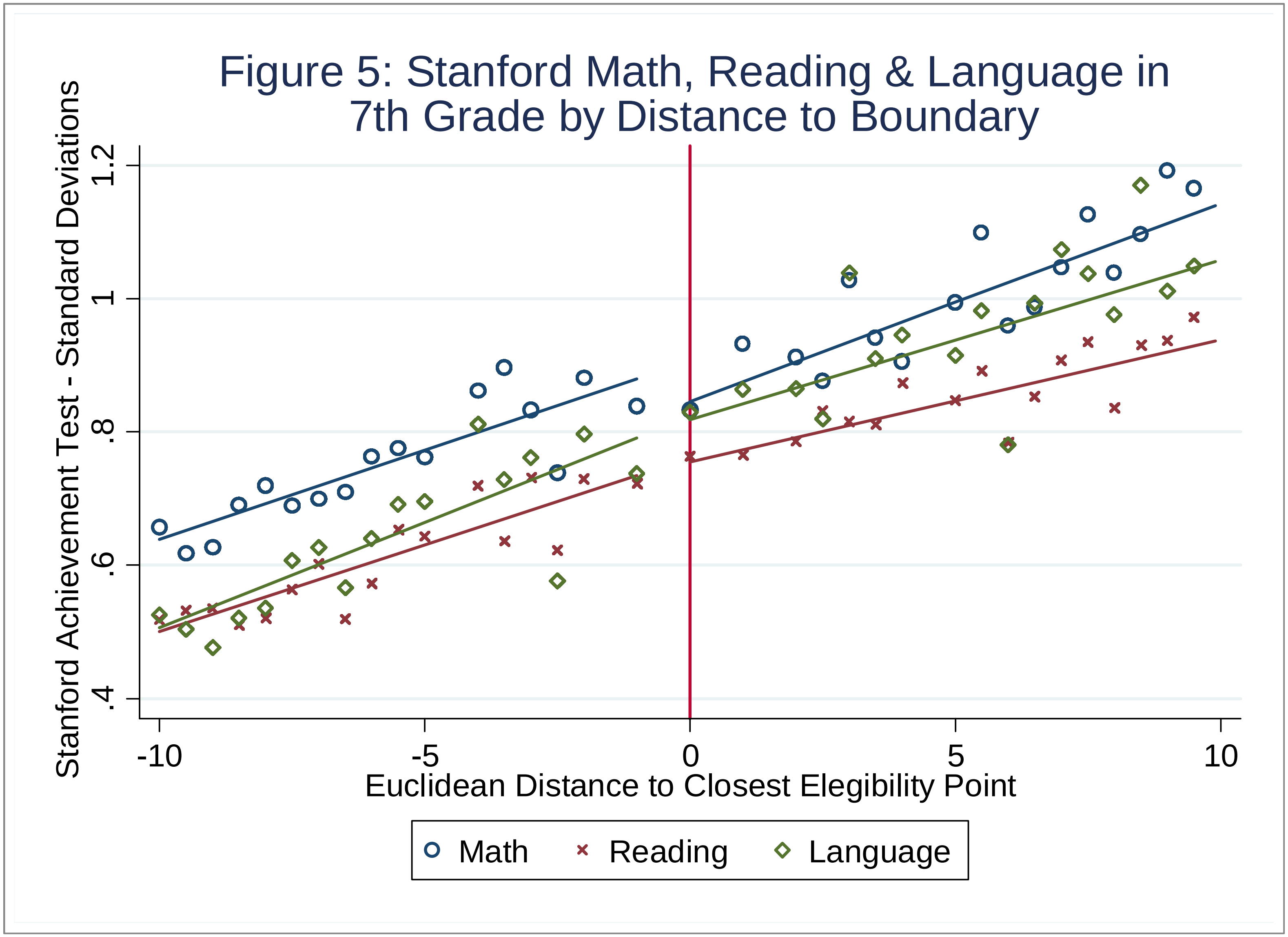


Figure 5: Stanford Math, Reading & Language in
7th Grade by Distance to Boundary
Stanford Achievement Test - Standard Deviations
.4
.6
.8
1
1.2
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point
Math
Reading
Language

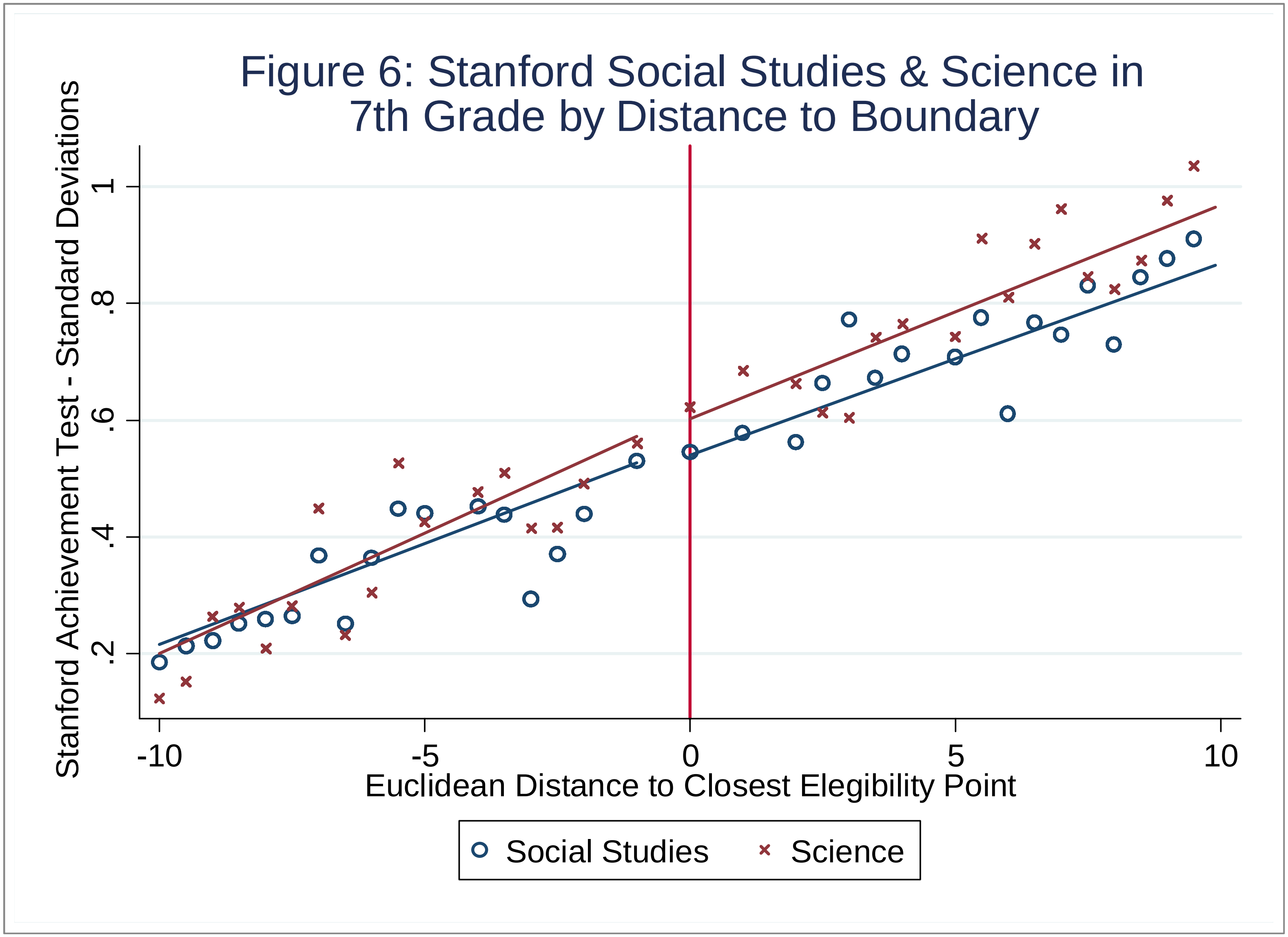


Figure 6: Stanford Social Studies & Science in 7th Grade by Distance to Boundary
Stanford Achievement Test - Standard Deviations
.2
.4
.6
.8
1
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point
Social Studies
Science

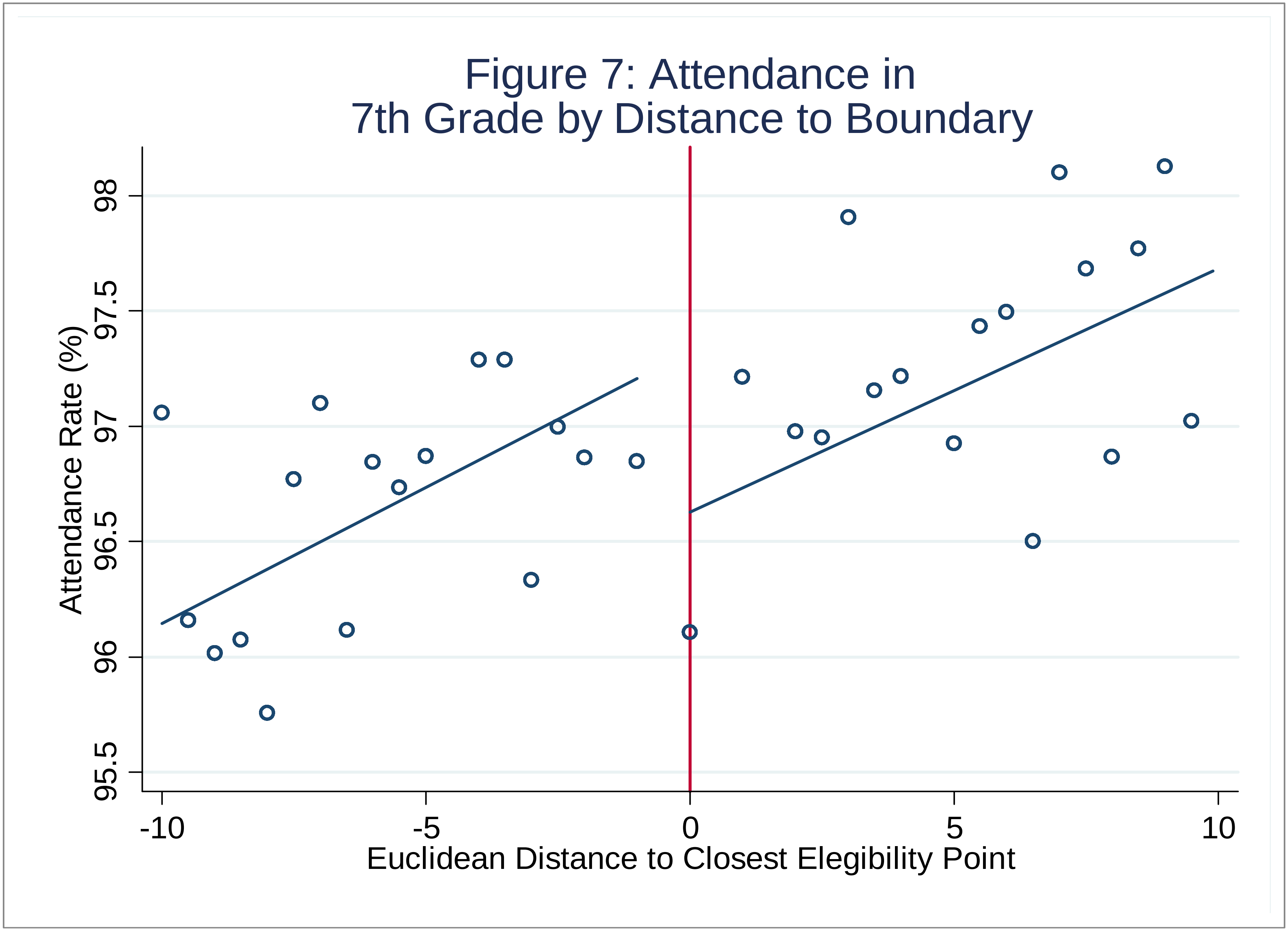


Figure 7: Attendance in
7th Grade by Distance to Boundary
Attendance Rate (%)
95.5
96
96.5
97
97.5
98
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point

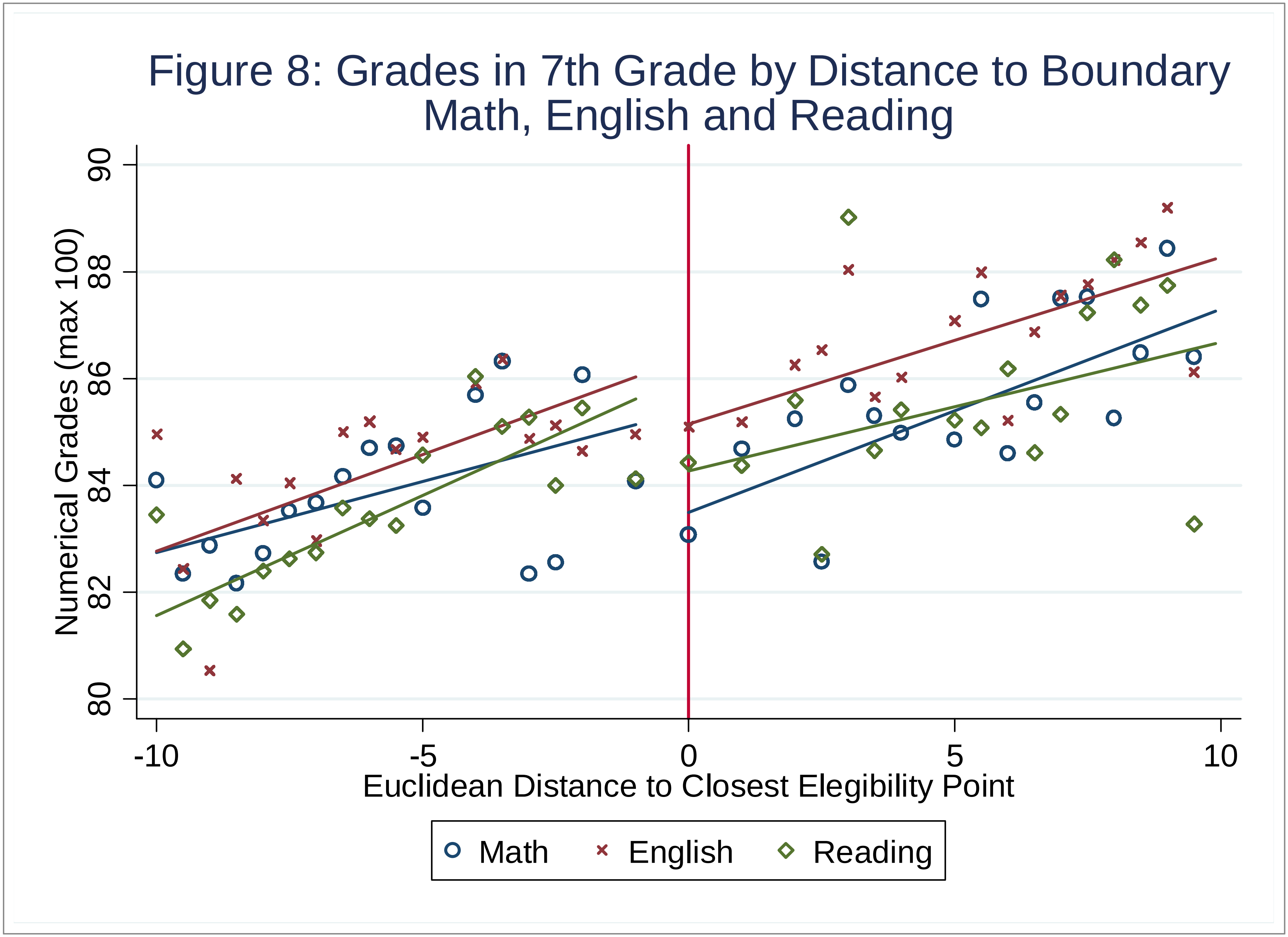


Figure 8: Grades in 7th Grade by Distance to Boundary
Math, English and Reading
Numerical Grades (max 100)
80
82
84
86
88
90
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point
Math
English
Reading

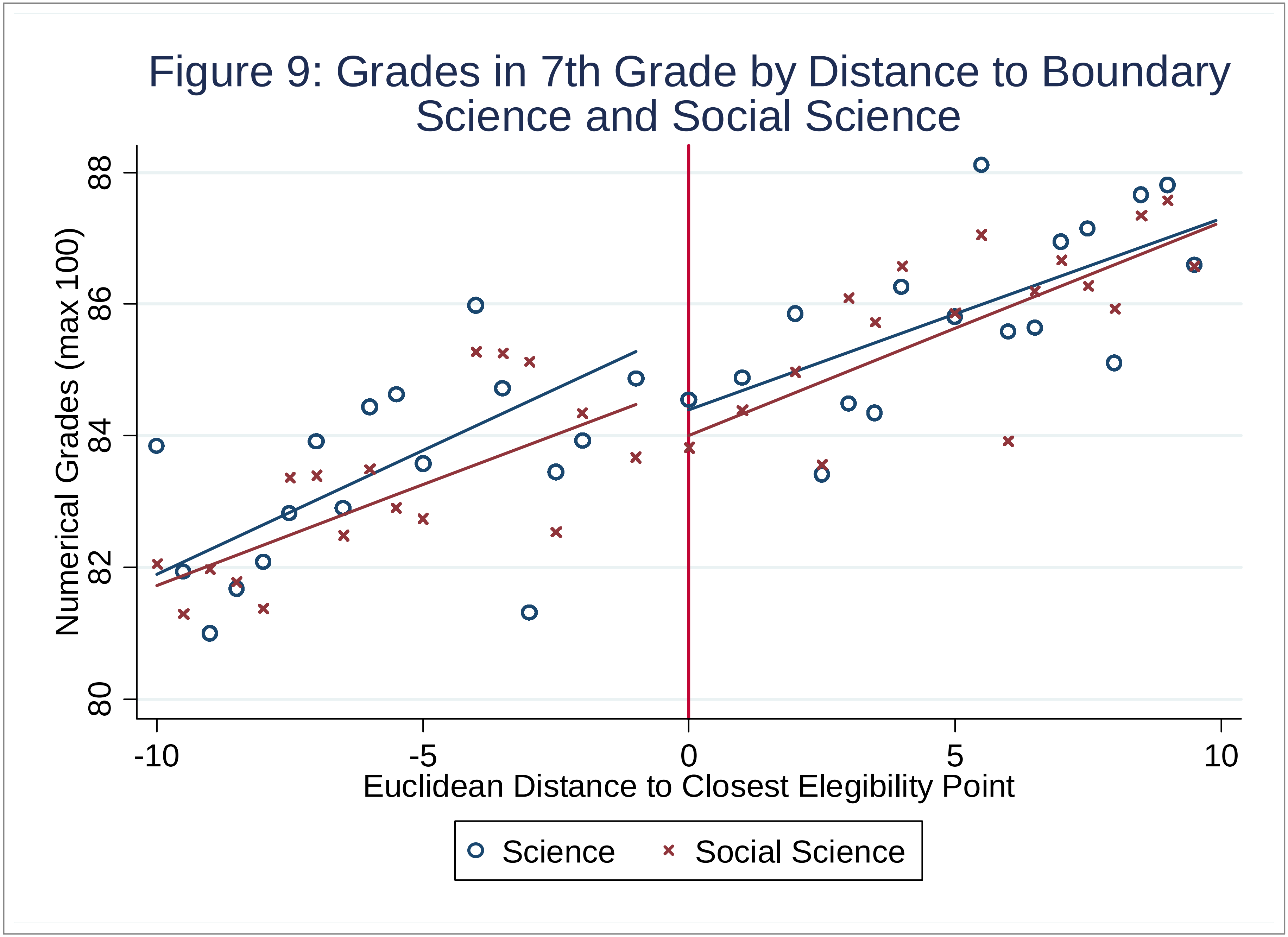


Figure 9: Grades in 7th Grade by Distance to Boundary
Science and Social Science
Numerical Grades (max 100)
80
82
84
86
88
-10
-5
0
5
10
Euclidean Distance to Closest Elegibility Point
Science
Social Science

Table 1 - Characteristics of Students Evaluated for Middle School GT in 2007-08

	I. Regression Discontinuity Sample			II. GT Magnet Lottery Sample		
	Gifted in 2009-10 (7th Grade)	Not Gifted in 2009-10	Not in Sample in 2009-10	In Magnet in 2009-10	Not in GT Magnet in 2009-10	Not in Sample in 2009-10
			A. 5th Grade Characteristics			
Female	0.54	0.48	0.50	0.51	0.54	0.57
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Economically Disadvantaged	0.59	0.89	0.81	0.24	0.41	0.17
	(0.49)	(0.31)	(0.39)	(0.43)	(0.49)	(0.37)
LEP	0.23	0.37	0.28	0.02	0.06	0.04
	(0.42)	(0.48)	(0.45)	(0.15)	(0.24)	(0.20)
Asian	0.11	0.02	0.03	0.28	0.16	0.19
	(0.31)	(0.13)	(0.18)	(0.45)	(0.37)	(0.39)
Black	0.13	0.28	0.33	0.12	0.21	0.18
	(0.34)	(0.45)	(0.47)	(0.32)	(0.41)	(0.38)
Hispanic	0.52	0.66	0.56	0.22	0.23	0.14
	(0.50)	(0.47)	(0.50)	(0.41)	(0.42)	(0.35)
White	0.24	0.04	0.09	0.38	0.40	0.50
	(0.43)	(0.19)	(0.28)	(0.49)	(0.49)	(0.50)
Gifted	0.68	0.06	0.15	0.85	0.85	0.83
	(0.47)	(0.25)	(0.36)	(0.36)	(0.36)	(0.37)
Stanford Math	0.74	0.06	0.18	1.61	1.39	1.72
	(0.59)	(0.39)	(0.47)	(0.79)	(0.71)	(1.03)
Stanford Reading	0.64	-0.02	0.11	1.72	1.60	1.83
	(0.41)	(0.39)	(0.47)	(0.78)	(0.77)	(0.87)
Stanford Language	0.74	-0.16	0.01	1.61	1.48	1.83
	(0.59)	(0.57)	(0.67)	(0.84)	(0.76)	(0.94)
Stanford Social Science	0.43	-0.61	-0.42	1.52	1.48	1.75
	(0.68)	(0.68)	(0.80)	(0.86)	(0.84)	(0.91)
Stanford Science	0.50	-0.50	-0.30	1.47	1.36	1.61
	(0.66)	(0.65)	(0.76)	(0.89)	(0.79)	(0.95)
Disciplinary Infractions	0.04	0.21	0.25	0.02	0.05	0.01
	(0.26)	(0.73)	(0.87)	(0.15)	(0.24)	(0.10)
Attendence Rate	98.26	97.25	96.58	98.35	97.98	97.00
	(2.35)	(4.52)	(4.95)	(2.00)	(2.34)	(3.75)
			B, 7th Grade Outcomes			
Stanford Math	1.11	-0.40	-	1.70	1.53	-
	(0.45)	(0.41)	-	(0.84)	(0.86)	-
Stanford Reading	0.95	-0.31	-	1.66	1.58	-
	(0.37)	(0.38)	-	(0.66)	(0.72)	-
Stanford Language	1.08	0.17	-	1.59	1.44	-
	(0.57)	(0.58)	-	(0.80)	(0.72)	-
Stanford Social Science	0.88	-0.09	-	1.70	1.51	-
	(0.64)	(0.60)	-	(0.88)	(0.80)	-
Stanford Science	1.00	-0.18	-	1.72	1.36	-
	(0.79)	(0.71)	-	(0.94)	(0.77)	-
Disciplinary Infractions	0.28	1.25	-	0.05	0.13	-
	(1.11)	(2.61)	-	(0.24)	(0.86)	-
Attendence Rate	97.37	95.02	-	97.84	97.57	-
	(3.19)	(6.13)	-	(2.52)	(3.16)	-
Observations	1,919	8,748	3,652	291	149	102

Standard deviations in parentheses. Achievement is measured in standard deviation units within grade and year across the district. Disciplinary infractions are the number of times a student is given a suspension or more severe punishment. Economically disadvantaged refers to students who qualify for free lunch, reduced-price lunch or another federal or state anti-poverty program.

Table 2 - Reduced-Form Estimates of Discontinuities in Pre-Existing (5th Grade) Student Characteristics

	Black	Hispanic	Female	LEP	Gifted in 5th Grade	Special Education	Free / Reduced-Price Lunch	Stanford - Math	Stanford - Reading	Stanford - Language
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Above GT Cutoff	-0.000	0.014	0.024	0.039	-0.050	0.005	0.049	-0.067***	0.006	0.006
	(0.029)	(0.038)	(0.042)	(0.040)	(0.047)	(0.011)	(0.037)	(0.026)	(0.026)	(0.041)
Observations	2,650	2,650	2,650	2,650	2,650	2,650	2,650	2,637	2,638	2,636

	Stanford - Social Studies	Stanford - Science	# of Disciplinary Infractions	Attendance Rate (%)	Any Missing Matrix Data	Teacher Score	Teacher Points	Enrolled	Enrolled (F/RP)	Enrolled (Non-F/RP)
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Above GT Cutoff	0.040	0.004	-0.001	-0.269	0.000	2.965	0.497	0.049	0.054	0.039
	(0.049)	(0.042)	(0.028)	(0.190)	(0.008)	(2.715)	(0.321)	(0.030)	(0.037)	(0.053)
Observations	2,636	2,637	2,650	2,650	2,650	2,648	2,648	3,438	2,177	1,261

Achievement measured in standard deviations of scale scores within grade and year. Disciplinary infractions is the number of infractions warranting a suspension or more severe punishment per year. Includes a linear smoother with a slope shift above the cutoff. Sample is limited to students with Euclidean distances from qualifying via the GT qualification matrix of between -10 and 10. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are robust to heteroskedasticity and clustered by 5th grade school. Sample is for columns (1) to (18) are for the estimation sample - students observed in LUSD two years after evaluation (7th grade). Tests using the full set of evaluated students provides similar results and is provided in the online appendix.

Table 3 - Regression Discontinuity Estimates of Impact of Receiving G&T Services

Model	Dependent Variable	Stanford Achievement Test: Math (1)	Reading (2)	Language (3)	Social Science (4)	Science (5)	Disciplinary Infractions (6)	Attendance Rate (%) (7)
A. Baseline								
Reduced Form	Above GT Cutoff	-0.061**	-0.005	-0.004	-0.020	-0.011	-0.006	-0.691**
		(0.030)	(0.029)	(0.044)	(0.038)	(0.060)	(0.120)	(0.311)
2SLS - 1st Stage	Above GT Cutoff	0.440***	0.443***	0.442***	0.440***	0.440***	0.436***	0.438***
		(0.057)	(0.057)	(0.058)	(0.058)	(0.057)	(0.058)	(0.058)
2SLS - 2nd Stage	**Enrolled in GT**	**-0.138****	**-0.011**	**-0.008**	**-0.045**	**-0.025**	**-0.014**	**-1.578***
		(0.068)	**(0.065)**	**(0.100)**	**(0.085)**	**(0.135)**	**(0.276)**	**(0.802)**
Observations		2,612	2,614	2,612	2,610	2,612	2,653	2,652
B. With Individual Controls								
Reduced Form	Above GT Cutoff	-0.016	-0.001	0.005	-0.007	0.008	0.003	-0.502*
		(0.022)	(0.020)	(0.031)	(0.031)	(0.048)	(0.112)	(0.268)
2SLS - 1st Stage	Above GT Cutoff	0.465***	0.457***	0.457***	0.454***	0.456***	0.451***	0.456***
		(0.060)	(0.061)	(0.061)	(0.061)	(0.061)	(0.060)	(0.060)
2SLS - 2nd Stage	**Enrolled in GT**	**-0.035**	**-0.002**	**0.010**	**-0.016**	**0.017**	**0.007**	**-1.101***
		(0.047)	**(0.044)**	**(0.068)**	**(0.068)**	**(0.106)**	**(0.248)**	**(0.653)**
Observations		2,597	2,600	2,596	2,594	2,597	2,650	2,649
C. Using Synthetic Matrix Scores								
Reduced Form	Above GT Cutoff	-0.024	-0.028	-0.028	-0.054	0.002	0.088	0.346
		(0.028)	(0.020)	(0.039)	(0.041)	(0.059)	(0.130)	(0.309)
2SLS - 1st Stage	Above GT Cutoff	0.229***	0.232***	0.230***	0.228***	0.229***	0.230***	0.229***
		(0.038)	(0.038)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)
2SLS - 2nd Stage	**Enrolled in GT**	**-0.106**	**-0.121**	**-0.120**	**-0.236**	**0.011**	**0.382**	**1.509**
		(0.122)	**(0.085)**	**(0.170)**	**(0.188)**	**(0.256)**	**(0.568)**	**(1.328)**
Observations		2,579	2,580	2,579	2,576	2,578	2,619	2,618

Achievement measured in standard deviations of scale scores within grade and year. Disciplinary infractions is the number of infractions warranting a suspension or more severe punishment per year. Synthetic matrix scores replace matrix scores for students where a teacher recommendation could be pivotal (e.g. total points w/o the recommendation is fewer than 10 away from the relevant cutoff) with the predicted value from a regression of total points on all components excluding the teacher points. See text for details. Controls for race, gender, economic

Table 4 - 2SLS Estimates of Impact of Receiving G&T Services
Estimates for Sub-Populations

			Stanford Achievement Test						
		First Stage (1)	Math (2)	Reading (3)	Language (4)	Social Science (5)	Science (6)	Disciplinary Infractions (7)	Attendance Rate (%) (8)
(1)	Females	0.531***	-0.023	-0.030	-0.028	-0.041	-0.003	0.177	-1.909**
		(0.063)	(0.054)	(0.049)	(0.068)	(0.083)	(0.114)	(0.230)	(0.726)
	Observations	1,336	1,336	1,335	1,335	1,333	1,336	1,361	1,360
(2)	Males	0.410***	-0.022	0.044	0.093	0.040	0.046	-0.205	0.029
		(0.076)	(0.081)	(0.061)	(0.106)	(0.110)	(0.147)	(0.495)	(1.119)
	Observations	1,237	1,237	1,240	1,236	1,237	1,237	1,260	1,260
(3)	Free/Reduced-Price Lunch	0.512***	0.009	-0.032	0.014	-0.016	-0.031	0.160	-0.895
		(0.064)	(0.050)	(0.047)	(0.079)	(0.083)	(0.113)	(0.306)	(0.671)
	Observations	1,644	1,644	1,645	1,644	1,644	1,645	1,669	1,669
(4)	No Free/Reduced-Price Lunch	0.366***	-0.126	0.076	0.000	-0.023	0.095	-0.613	-1.370
		(0.088)	(0.097)	(0.076)	(0.130)	(0.177)	(0.178)	(0.606)	(1.367)
	Observations	929	929	930	927	926	928	952	951
(5)	Black	0.605***	-0.068	0.124	-0.100	0.092	0.092	-0.181	-2.006*
		(0.116)	(0.082)	(0.081)	(0.144)	(0.154)	(0.177)	(0.366)	(1.027)
	Observations	435	435	435	435	433	434	447	447
(6)	Hispanic	0.453***	-0.024	-0.032	0.058	-0.043	0.048	-0.067	-1.109
		(0.059)	(0.066)	(0.057)	(0.087)	(0.086)	(0.126)	(0.400)	(0.865)
	Observations	1,680	1,680	1,682	1,679	1,679	1,680	1,708	1,708
(7)	White	0.289	0.015	-0.195	0.014	0.093	-0.446	-0.151	2.301*
		(0.183)	(0.257)	(0.221)	(0.277)	(0.375)	(0.529)	(0.513)	(1.285)
	Observations	325	325	325	325	325	326	330	329
(8)	Gifted in 5th Grade	0.368***	-0.096	0.033	0.182	0.093	0.129	0.699	-2.041
		(0.082)	(0.102)	(0.095)	(0.124)	(0.159)	(0.230)	(0.558)	(1.421)
	Observations	1,003	1,003	1,005	1,004	1,003	1,004	1,017	1,016
(9)	Not Gifted in 5th Grade	0.534***	-0.003	-0.005	-0.045	-0.035	-0.027	-0.291	-0.666
		(0.071)	(0.056)	(0.053)	(0.077)	(0.090)	(0.122)	(0.288)	(0.636)
	Observations	1,570	1,570	1,570	1,567	1,567	1,569	1,604	1,604

Achievement measured in standard deviations of scale scores within grade and year. Disciplinary infractions is the number of infractions warranting a suspension or more severe punishment per year. Controls for race, gender, economic disadvantage and lagged (5th grade) dependent varable included, along with a linear smoother with a slope shift above the cutoff included. Standard errors are robust to heteroskedasticity and clustered by 7th grade school. Sample is limited to students with Euclidean distances from qualifying via the GT qualification matrix of between -10 and 10.

Table 5 - 2SLS Regression Discontinuity Estimates of Impact of Receiving G&T Services
Specification Checks

		Stanford Achievement Test						
	First Stage	Math	Reading	Language	Social Science	Science	Disciplinary Infractions	Attendance Rate (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Quadratic Smoother	0.424***	0.120	0.007	0.246**	0.146	0.305*	-0.445	-0.565
	(0.063)	(0.112)	(0.071)	(0.111)	(0.135)	(0.159)	(0.505)	(1.253)
Observations	2,609	2,597	2,600	2,596	2,594	2,597	2,650	2,649
(2) Cubic Smoother	0.371***	0.057	-0.029	0.276	-0.019	0.409	-0.617	-0.455
	(0.103)	(0.238)	(0.157)	(0.203)	(0.244)	(0.332)	(0.745)	(2.036)
Observations	2,609	2,597	2,600	2,596	2,594	2,597	2,650	2,649
(3) Add Middle School Fixed Effects	0.460***	-0.014	0.007	0.041	0.009	0.023	0.067	-1.039*
	(0.057)	(0.037)	(0.041)	(0.065)	(0.065)	(0.112)	(0.249)	(0.600)
Observations	2,609	2,597	2,600	2,596	2,594	2,597	2,650	2,649
(4) Limited to Observations With	0.456***	-0.027	0.003	0.013	-0.004	0.029	0.068	-1.186*
No Missing Matrix Data	(0.061)	(0.048)	(0.044)	(0.067)	(0.068)	(0.108)	(0.263)	(0.684)
Observations	2,538	2,526	2,528	2,525	2,522	2,525	2,577	2,576
(6) Distance Between -4 & 4	0.387***	0.116	-0.097	0.132	-0.029	0.338	-0.762	-0.835
	(0.084)	(0.167)	(0.111)	(0.159)	(0.170)	(0.246)	(0.518)	(1.647)
Observations	849	845	848	845	842	844	860	859
(5) Distance Between -8 & 8	0.462***	0.005	0.014	0.111	0.056	0.115	-0.162	-0.638
	(0.056)	(0.058)	(0.046)	(0.072)	(0.080)	(0.103)	(0.325)	(0.758)
Observations	2,057	2,047	2,052	2,047	2,044	2,047	2,084	2,083
(6) Distance Between -12 & 12	0.472***	-0.009	0.018	-0.013	0.007	0.019	0.001	-0.823
	(0.055)	(0.039)	(0.036)	(0.057)	(0.063)	(0.086)	(0.209)	(0.549)
Observations	3,178	3,162	3,163	3,158	3,158	3,160	3,222	3,220
(6) Distance Between -16 & 16	0.488***	-0.022	0.009	-0.015	-0.022	0.017	0.100	-0.438
	(0.055)	(0.035)	(0.030)	(0.045)	(0.061)	(0.077)	(0.179)	(0.497)
Observations	3,756	3,735	3,736	3,731	3,729	3,733	3,806	3,804
(7) Local Linear Regressions	-	0.073	0.000	0.019	0.056	0.222	1.476	-0.434
with Rectangular Kernel	-	(0.117)	(0.072)	(0.186)	(0.080)	(0.177)	(1.002)	(1.203)
Observations	-	1,075	1,078	708	2,044	1,074	429	1,092
Bandwidth (from Leave-One-Out Cross Validation)	-	5	5	3	8	5	2	5

Achievement measured in standard deviations of scale scores within grade and year. Disciplinary infractions is the number of infractions warranting a suspension or more severe punishment per year. Controls for race, gender, economic disadvantage, LEP, prior gifted status and lagged (5th grade) dependent varable included and a linear smoother with a slope shift above the cutoff except where noted.. Sample is limited to students with Euclidean distances from qualifying via the GT qualification matrix of between -10 and 10. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are robust to heteroskedasticity and clustered by 7th grade school.

Table 6 - 2SLS Estimates of Impacts of G&T Services
Effects on Educational Environment and Student Choices

	Peer Math Scores in Math Classes (1)	Peer Reading Scores in Read/Eng Classes (2)	Peer Lang Scores in Read/Eng Classes (3)	Peer Soc Scores in Soc Classes (4)	Peer Science Scores in Science Classes (5)	# of Core Regular Classes (6)	# of Core Vanguard Classes (7)	Enrolled in Vanguard Math (8)	Enrolled in Vanguard English (9)
Enrolled in GT	0.348**	0.287*	0.311**	0.235*	0.272*	-0.014	1.145*	0.315*	0.241
	(0.166)	(0.156)	(0.146)	(0.132)	(0.150)	(0.267)	(0.624)	(0.158)	(0.171)
Observations	2,629	2,494	2,494	2,567	2,567	2,643	2,643	2,629	2,497

	Enrolled in Vanguard Social Science (10)	Enrolled in Vanguard Science (11)	Attends Zoned School (12)	Attends Non-Zoned GT Magnet Campus (13)	Attends Other Non-Zoned (14)	Math Teacher Fixed Effect (15)	Read/Eng Teacher Fixed Effect (16)	Science Teacher Fixed Effect (17)	Social Science Teacher Fixed Effect (18)
Enrolled in GT	0.282*	0.282*	-0.050	0.260**	-0.210**	-0.001	0.016	0.005	0.014
	(0.165)	(0.165)	(0.109)	(0.109)	(0.098)	(0.025)	(0.010)	(0.014)	(0.013)
Observations	2,567	2,567	2,623	2,623	2,623	2,650	2,621	2,621	2,621

Achievement measured in standard deviations of scale scores within grade and year. Teacher fixed effects are estimates from a student-level regression of achievement on lagged achievement, peer lagged achievement, race, gender, special education, LEP, at-risk status, teacher fixed-effects and school fixed-effects. Controls for race, gender, economic disadvantage, LEP, prior gifted status and lagged (5th grade) dependent varable included. Also includes a linear smoother with a slope shift above the cutoff. Peers are defined by teacher-course id-grade cells. Sample is limited to students with Euclidean distances from qualifying via the GT qualification matrix of between -10 and 10. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are robust to heteroskedasticity and clustered by 7th grade school.

Table 7 - 2SLS Estimates of Impacts of G&T Services
Effects on Course Grades (2007-08 Evaluation Cohort)

	Math	English	Reading	Social Studies	Science
	(1)	(2)	(3)	(5)	(4)
	A. 7th Grade				
Enrolled in GT	-4.142**	-2.621	-4.048*	-1.501	-2.473
	(1.616)	(1.744)	(2.062)	(1.052)	(1.645)
Observations	2,643	2,510	1,439	2,602	2,581
	B. 6th Grade				
Enrolled in GT	-3.516***	-1.939	-2.698*	-3.395**	-3.002**
	(1.177)	(1.489)	(1.373)	(1.438)	(1.353)
Observations	2,734	2,604	2,608	2,728	2,749

Achievement measured in standard deviations of scale scores within grade and year. Controls for race, gender, economic disadvantage, LEP, and prior gifted status are included along with a linear smoother with a slope shift above the cutoff. Sample is limited to students with Euclidean distances from qualifying via the GT qualification matrix of between -10 and 10. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are robust to heteroskedasticity and clustered by 7th grade school.

Table 8 - Balancing Tests for GT Magnet Lotteries - Covariates Measured in 5th Grade

Sample	Asian (1)	Black (2)	Hispanic (3)	White (4)	Econ Disadv (5)	Female (6)	At-Risk (7)	Special Education (8)	LEP (9)	Gifted (10)
Ex-Ante - Baseline Lottery	-0.030	0.030	0.041	-0.041	-0.035	-0.006	-0.011	-0.019	-0.033	-0.028
	(0.044)	(0.038)	(0.044)	(0.050)	(0.045)	(0.047)	(0.010)	(0.017)	(0.022)	(0.035)
Observations	542	542	542	542	542	542	542	542	542	542
Ex-Post - Estimation Sample	-0.027	0.041	0.042	-0.057	-0.050	-0.001	-0.009	-0.015	-0.031	-0.024
	(0.048)	(0.038)	(0.055)	(0.056)	(0.059)	(0.052)	(0.011)	(0.023)	(0.027)	(0.047)
Observations	437	437	437	437	437	437	437	437	437	437

			Stanford Achievement Test							
Sample	GT Magnet (11)	Total Matrix Points (12)	Math (13)	Reading (14)	Language (15)	Social Studies (16)	Science (17)	Attendance Rate (18)	Infractions (19)	Teacher Score (20)
Ex-Ante - Baseline Lottery	0.035	0.243	0.027	0.073	-0.034	0.053	0.010	-0.180	-0.022	0.029
	(0.030)	(0.926)	(0.069)	(0.063)	(0.077)	(0.089)	(0.076)	(0.201)	(0.021)	(1.304)
Observations	542	542	540	541	539	540	539	542	542	536
Ex-Post - Estimation Sample	0.055	0.909	0.128*	0.100	-0.059	0.063	0.090	-0.064	-0.022	-1.005
	(0.045)	(1.173)	(0.074)	(0.075)	(0.077)	(0.096)	(0.088)	(0.230)	(0.025)	(1.471)
Observations	437	437	437	437	436	437	436	437	437	434

Achievement measured in standard deviations of scale scores within grade and year. Disciplinary infractions is the number of infractions warranting a suspension or more severe punishment per year. Lotteries for two schools were conducted in 2007-08 hence regresions include indicators for lottery fixed effects. Coefficients are for an indicator for whether the student won the lottery. Robust standard errors clustered by 5th grade school in parentheses. Results without clustering are similar and provided in the online appendix.

Table 9 - Effect of Attending a GT Magnet School Relative to a GT Neighborhood Progran

Model	Stanford Achievement Test					Attendence Rate
	Math	Reading	Language	Social Studies	Science	(%)
	(1)	(2)	(3)	(4)	(5)	(6)
2SLS - Unweighted, No Controls	0.042	0.023	0.102	0.039	0.249**	-0.434
	(0.178)	(0.103)	(0.065)	(0.083)	(0.114)	(0.636)
Observations	437	438	436	437	437	440
2SLS - Unweighted, Controls	-0.100	-0.058	0.142*	-0.032	0.208*	-0.425
	(0.112)	(0.105)	(0.081)	(0.098)	(0.119)	(0.411)
Observations	437	438	436	437	437	440
2SLS - Weighted, No Controls	-0.266	-0.130	-0.060	-0.120	0.243	0.043
	(0.291)	(0.221)	(0.148)	(0.214)	(0.201)	(1.996)
Observations	436	437	435	436	436	439
2SLS - Weighted, Controls	-0.224	-0.018	0.001	-0.036	0.281**	0.364
	(0.171)	(0.172)	(0.114)	(0.136)	(0.130)	(1.489)
Observations	436	437	435	436	436	439
Engberg, Epple, Imbrogno, Sieg, Zimmer	-0.019	-0.095	0.074	-0.064	0.344*	-
(2011) Bounds - Upper Bound	(0.196)	(0.157)	(0.162)	(0.185)	(0.180)	-
Observations	437	438	436	437	437	-
Engberg, Epple, Imbrogno, Sieg, Zimmer	-0.353	-0.310	-0.207	-0.389	-0.013	-
(2011) Bounds - Lower Bound	(0.251)	(0.192)	(0.215)	(0.249)	(0.248)	-
Observations	437	438	436	437	437	-

Achievement measured in standard deviations of scale scores within grade and year. Lotteries for two schools were conducted in 2007-08 hence all regresions include indicators for lottery fixed effects. Coefficients are for an indicator for whether the student is enrolled in a GT magnet program in 7th grade. Robust standard errors clustered by 7th grade school in parentheses. Results without clustering are similar and provided in the online appendix. Controls include indicators during 5th grade for race, gender, special education, LEP, at-risk status, gifted, whether the student was enrolled in a GT magnet, and a lagged dependent variable. Weighted regressions are weighted by the inverse of the estimated probability of remaining in the data. See text for details. In order to avoid slow convergence due to a very small portion of the sample being in special education or LEP, we drop those controls from the bounding analysis. Additionally, we do not cluster the standard errors on the bounding analysis due to inability for the estimator to converge. Finally, we do not provide bounds for attendance due to poor performance with censored data. See pape

Table 10 - Treatments from Attending a GT Magnet School Relative to a GT Neighborhood Program

Model	Mean Peer Achievement (Std Deviations)					Teacher Fixed Effects	
	Math in Math Class	Reading in English Class	Language in English Class	Social Studies in Soc Class	Science in Science Class	Math	English/ Reading
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2SLS - Unweighted, Controls	1.066***	0.659***	0.579***	0.794***	0.524***	0.081***	0.032**
	(0.145)	(0.149)	(0.120)	(0.123)	(0.122)	(0.015)	(0.013)
Observations	440	436	436	439	439	440	440
2SLS - Weighted, Controls	1.164***	0.751***	0.686***	0.952***	0.659***	0.085***	0.032***
	(0.179)	(0.172)	(0.143)	(0.180)	(0.166)	(0.019)	(0.011)
Observations	439	435	435	438	438	439	439
	Teacher Fixed Effects		Course Grades				
	Social Studies	Science	Math	English	Social Studies	Science	
	(8)	(9)	(10)	(11)	(12)	(13)	
2SLS - Unweighted, Controls	0.031*	0.017	-8.283***	-4.096**	-4.062**	-6.988***	
	(0.017)	(0.014)	(1.660)	(1.561)	(1.654)	(1.309)	
Observations	440	440	440	437	439	439	
2SLS - Weighted, Controls	0.041**	0.016	-7.311***	-2.719	-4.733**	-8.121***	
	(0.019)	(0.013)	(1.847)	(1.990)	(1.733)	(2.297)	
Observations	439	439	439	436	438	438	

Achievement measured in standard deviations of scale scores within grade and year. Teacher fixed effects are estimates from a student-level regression of achievement on lagged achievement, peer lagged achievement, race, gender, special education, LEP, at-risk status, teacher fixed-effects and school fixed-effects. Lotteries for two schools were conducted in 2007-08 hence all regresions include indicators for lottery fixed effects. Coefficients are for an indicator for whether the student is enrolled in a GT magnet program in 7th grade. Peers are defined by teacher-course id-grade cells. Robust standard errors clustered by 7th grade school in parentheses. Results without clustering are similar and provided in the online appendix. Weighted regressions are weighted by the inverse of the estimated probability of remaining in the data. See text for details. Controls include indicators during 5th grade for race, gender, special education, LEP, at-risk status, gifted, whether the student was enrolled in a GT magnet, and a lagged dependent variable.

Table 11 - 2SLS Estimates of the Effect of Attending a GT Magnet School Relative to a GT Neighborhood Program, Subpopulations Weighted with Controls

Subpopulation	Stanford Achievement Test					Attendence
	Math	Reading	Language	Social Studies	Science	Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.171	0.023	-0.186	0.033	0.183	-0.838**
	(0.154)	(0.269)	(0.151)	(0.100)	(0.138)	(0.334)
Observations	229	229	229	229	229	231
Male	-0.007	0.025	0.237	0.044	0.258	2.198
	(0.175)	(0.156)	(0.248)	(0.172)	(0.208)	(2.752)
Observations	207	208	206	207	207	208
White	-0.182	-0.171	0.296*	-0.013	0.347*	-0.100
	(0.123)	(0.128)	(0.152)	(0.205)	(0.159)	(0.449)
Observations	172	172	172	172	172	172
Minority	-0.032	0.103	-0.131	0.067	0.200	0.788
	(0.192)	(0.165)	(0.163)	(0.095)	(0.155)	(2.016)
Observations	264	265	263	264	264	267
Minority - Excluding Asians	0.063	0.356	-0.327	0.072	-0.001	-0.634**
	(0.220)	(0.210)	(0.238)	(0.136)	(0.116)	(0.245)
Observations	158	159	157	158	158	161
Not Economically Disadvantaged	-0.152	-0.053	0.320**	-0.034	0.291	-0.551
	(0.166)	(0.137)	(0.119)	(0.189)	(0.186)	(0.442)
Observations	307	308	307	307	307	309
Economically Disadvantaged	-0.041	0.124	-0.230	0.065	0.245	0.915
	(0.217)	(0.233)	(0.178)	(0.093)	(0.183)	(2.027)
Observations	129	129	128	129	129	130
Below Median Achievement of Lottery	0.026	-0.217	-0.169	-0.123	0.237***	-
Participants	(0.249)	(0.279)	(0.205)	(0.155)	(0.056)	-
Observations	208	200	177	222	205	-
Above Median Achievement of Lottery	-0.049	0.062	0.290*	-0.025	0.340	-
Participants	(0.135)	(0.178)	(0.151)	(0.194)	(0.240)	-
Observations	228	237	258	215	231	-
Below 25th Percentile of Achievement	-0.042	-0.533**	0.085	-0.010	0.010	-
for Lottery Participants	(0.200)	(0.209)	(0.163)	(0.207)	(0.151)	-
Observations	97	112	93	98	88	-
Above 75th Percentile of Achievement	-0.204	0.306	0.477	0.183	0.614	-
for Lottery Participants	(0.176)	(0.358)	(0.282)	(0.341)	(0.436)	-
Observations	111	135	141	111	89	-

Achievement measured in standard deviations of scale scores within grade and year. Achievement percentiles are for fully baseline lottery sample using 5th grade achievment in same subject. Lotteries for two schools were conducted in 2007-08 hence all regresions include indicators for lottery fixed effects. Coefficients are for an indicator for whether the student is enrolled in a GT magnet program in 7th grade. Robust standard errors clustered by 7th grade school in parentheses. Results without clustering are similar and provided in the online appendix. Regressions are weighted by the inverse of the estimated probability of remaining in the data. See text for details. Controls include indicators during 5th grade for race, gender, special education, LEP, at-risk status, gifted, whether the student was enrolled in a GT magnet, and a lagged dependent variable.