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The Impact of Peers on Cognitive, Non-cognitive, and Behavioural Outcomes

Evidence from India

Uteeyo Dasgupta
Subha Mani
Smriti Sharma
Saurabh Singhal

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The Impact of Peers on Cognitive, Non-Cognitive, and Behavioral Outcomes: Evidence from India[a]

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UTTEEYO DASGUPTA[1], SUBHA MANI[2], SMRITI SHARMA[3], SAURABH SINGHAL[4]

Abstract

In this paper, we exploit the variation in the University of Delhi college admission process to estimate the effects of exposure to high achieving peers on cognitive attainment using scores on standardized university level examinations; behavioral outcomes such as risk preference, competitiveness, and confidence; and non-cognitive outcomes using measures of Big Five personality traits. Using a regression discontinuity design, we find that the eligibility to enroll in a better quality college (proxied by peer ability) has a positive effect on cognitive outcomes with larger and more consistent effects for females than males. We also find that exposure to high achieving peers has an effect on selected personality traits and behavioral outcomes. To the best of our knowledge, this is the first paper in the literature to go beyond cognitive outcomes, and also causally identify the effects of exposure to high achieving peers on non-cognitive and behavioral outcomes.

Keywords: Cognitive outcomes, Behavioral outcomes, Personality traits, College quality, Peer effects, Extra-lab experiments, India

JEL Classification Codes: I23, C9, C14, J24, O15

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[1] Department of Economics, Wagner College, NY, USA, utteeyodasgupta@gmail.com

[2] Department of Economics and Center for International Policy Studies, Fordham University, NY, USA; Population Studies Center, University of Pennsylvania, PA, USA; IZA, Bonn, Germany, smani@fordham.edu

[3] UNU-WIDER, Helsinki, Finland, smriti@wider.unu.edu

[4] UNU-WIDER, Helsinki, Finland, saurabh@wider.unu.edu

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1. Introduction

The returns to college quality have been largely examined using measures of labor market performance and academic achievement. While most papers find positive and significant effects of enrollment in elite colleges on wages and employment outcomes (e.g., Hoekstra, 2009; Saavedra, 2009; Sekhri, 2013), the evidence on the returns to enrollment in elite colleges on performance in college exit examinations remains mixed. While Sekhri and Rubinstein (2011), Dale and Krueger (2002), Black and Smith (2004) and Dale and Krueger (2011) find that better quality colleges have no value added in terms of college grades, others such as Long (2008), Saavedra (2009) and Li et al. (2012) find significant benefits.[1] While these primarily focus on the cognitive aspects of human capital, another critical aspect, namely behavioral preferences and personality traits, often as important in determining labor market success and well being (Heckman et al., 2006; Lindqvist and Vestman, 2011; Borghans et. al, 2008; Bowles et al., 2001), have not yet been rigorously examined in this context.[2]

The objective of this paper is to close the existing gap in the literature by examining the returns to exposure to high achieving peers on not just cognitive outcomes, but also on non-cognitive outcomes that include behavioral preferences and personality traits. In doing so, we use a regression discontinuity design to address the selection bias problem arising from the non-random nature of college enrollment (and peer exposure).

We combine data from a series of unique incentivized extra-lab experiments and socioeconomic surveys administered to over 2000 undergraduate students at the University of Delhi (DU), one of the top universities in India, to estimate the effects of exposure to high achieving peers on three sets of outcomes. The first set of

[1] Similar conclusions emerge from papers that examine the returns to enrollment in more selective schools on academic performance (Ajayi (2014), Abdulkadiroğlu, Angrist and Pathak (2014), Berkowitz and Hoekstra (2011), Filmer and Schady (2014), Jackson (2010), Lucas and Mbiti (2014), Ozier (2011), and Pop-Eleches and Urquiola (2013)).

[2] For instance, Sekhri (2013) due to lack of data that directly measures soft skills, tries to infer this using variables such as reading newspapers, helping others with college work, winning awards etc. which may not be the most appropriate measures of personality traits.

outcomes includes measures of cognitive attainment such as scores on standardized university-level semester examinations. Academic performance and cognitive skills in general are well-established predictors of labor productivity and earnings (see Glewwe, 2002 and Hanushek and Woessmann, 2008 for reviews of this literature).

Second, we also examine the effects of exposure to high achieving peers on behavioral outcomes such as risk preference, competitiveness, and confidence. These behavioral outcomes have previously been shown to explain important labor market outcomes. For instance, gender differences in competitiveness have been shown to explain gender gaps in wages (Niederle and Vesterlund, 2007), job-entry decisions (Flory et al., 2015), and educational choices (Buser et al., 2014). The level of confidence also positively affects wages (Fang and Moscarini, 2005) and entrepreneurial behavior (e.g., Koellinger et al. 2007; Camerer and Lovallo, 1999). Castillo et al. (2010) find that risk preferences have implications for occupational sorting.

Finally, we also examine the impact of high achieving peers on Big Five personality traits. Borghans et al. (2008) document the importance of Big Five conscientiousness as an important predictor of years of education, grades, and job performance. Evidence from psychology suggests that personality traits develop through adolescence and young adulthood with changes in personality being most strong before one reaches working age (Cobb-Clark and Schurer, 2012, 2013; Specht et al., 2011). Schurer et al. (2015) estimate the returns to college education on personality (as measured by Big Five) using Australian data and find substantial variation in the influence of college enrollment on the Big Five personality traits.

We measure the impact of exposure to peers by using data on enrollment of students in different colleges of DU that vary in terms of their selectivity as determined by their admission criterion. Typically, obtaining the causal effect of enrolling in better quality colleges can be a challenge, as students are not randomly assigned to colleges and there is significant selection into colleges based on student ability. The admission criterion for colleges in DU allows us to exploit a regression discontinuity (RD) design. Students' report average scores on national high school exit examinations to apply to colleges and disciplines of their choice in DU and each college then declares discipline-specific cutoffs such that all students with scores above the cutoff are eligible to take admission in that college-discipline. We exploit students' inability to manipulate this admission cutoff and compare students just above and below the cutoff to determine the impact of their eligibility to enroll in a better quality college, such that the marginal student to the right of the cutoff is surrounded by high-achieving peers.

To the best of our knowledge, this is the first paper in the literature to use a RD design to examine the effects of exposure to college quality on cognitive, behavioral, and non-cognitive aspects of human capital. Our results indicate that exposure to high achieving peers leads to gains in scores on standardized university-level semester examinations, in particular for females. We also find that exposure to these peers has an effect on risk preferences for females such that females become less risk-averse. Further, we find that males exposed to high achieving peers are less likely to be open to experience. We find no significant effect of peer exposure on other personality traits and behavioral outcomes. We find higher attendance rates among females to be one of the likely channels explaining the gender differences in returns to better peer environment. Our results are robust to number of checks prescribed in the RD design literature.

The rest of the paper is organized as follows. We provide a description of the college admissions process, sampling strategy, subject recruitment, and data in Section 2. The empirical specification is outlined in Section 3. The main results are presented in Section 4 and robustness checks are presented in Section 5. Finally, concluding comments follow in Section 6.

2. Background and Data

2.1 College Admissions Process

Our sample of interest is 2nd and 3rd year students enrolled in the 3-year undergraduate degree program in the DU, which includes 79 affiliated colleges with considerable variation in quality.

In DU, college admission for most disciplines is based solely on an average score computed as the best of four out of five subjects (including language) taken during the students' high school exit examination at the end of class 12. Students simultaneously apply to colleges and disciplines (within those colleges) of their choice in the month of June each year. Based on capacity constraints and the incoming cohort's average score, each discipline within a college then announces the cutoff scores that determine admission into the specific college and discipline.[3] All those above the cutoff in the discipline are eligible to take admission in the college-discipline. Since there is greater demand for better quality colleges and they are oversubscribed, the cutoffs for these colleges are significantly and systematically higher than the low-quality colleges, usually across several disciplines. If there are vacancies, the college gradually lowers the cutoff through a number of rounds until all spots are filled. As expected, the better quality colleges fill their seats within the first couple of rounds while the lower quality colleges sequentially lower their cutoffs, taking at times up to 10 such rounds to fill their seats. This real-life allocation mechanism is equivalent to the Gale and Shapley (1962) college-proposing mechanism and the resulting matching is stable (for a review, see Sönmez and Ünver, 2011). This process results in an allocation where typically the high achieving students attend the better quality colleges while the low achieving students get admitted to the lower quality colleges. This also results in a discontinuity in the probability of enrollment into a better quality college at the cutoff. We exploit this discontinuity in the admission process and compare the cognitive, behavioral, and personality outcomes of 2nd and 3rd year college students just above the cutoff to those just below the cutoff to compute the impact of the eligibility to enroll in a better quality college on these outcomes.

Due to the design of the admissions process in DU, students who are eligible to enroll in a better quality college are exposed to better quality peers who have substantially higher average scores on the high school exit examinations compared to students enrolled in lower quality colleges (See Figure 1).

2.2 Sampling Strategy and Recruitment of Subjects

[3] These cut-offs are publicly available at http://www.du.ac.in/index.php?id=664

We constructed our sample in the following manner. First, to ensure representation of colleges at both the high and low end of the college quality spectrum, we obtained the list of all 79 colleges affiliated with DU. Second, we drew a list of 58 colleges that offer courses in the commerce and arts streams. The 58 colleges that offer courses in these two streams can be further categorized into: morning coeducational colleges (31), morning women only colleges (10) and evening colleges (17). We further restrict ourselves to the coeducational colleges, as they are far more over-subscribed than the evening and women colleges. Furthermore, the lack of variation in college cutoffs among the women colleges makes it difficult to obtain a sufficient number of colleges both above and below the cutoffs. Of the 31 morning colleges, we further rule out colleges that offer too few courses or use religious criteria or any criteria other than the average class 12th examination scores for admission purposes, resulting in a list of 25 target colleges. After considering admission cutoffs for each of these 25 colleges for three consecutive years (2011-13), we identified 18 colleges that had consistently ranked admission cutoffs across the three years for the two disciplines of economics and commerce. These two disciplines are the most popular and competitive disciplines and have significantly higher levels of enrollment compared to other disciplines. We targeted 17 of these identified colleges, of which we were able to implement our study in 15 colleges with varying cutoffs. We conducted the study with 2065 2nd and 3rd year students in these 15 colleges during January-March 2014 in regular class hours, in coordination with the respective teachers.

2.3 Extra-lab Experiments and Survey

In the first part of the study, we conducted incentivized extra-lab experiments to obtain measures of behavioral outcomes. [4] First, to capture subjects' competitiveness and confidence we used a simple number-addition task (similar to Niederle and Vesterlund, 2007). After a practice session, participants had to predict their performances in advance, and also choose between a piece-rate and tournament compensation scheme. Under the piece-rate scheme, Rs. 10 was paid for every correct answer. Under the tournament scheme, Rs. 20 was paid for every correct

[4] Subject instructions for the experimental module are available from the authors upon request.

answer if the subject out-performed a randomly selected student of DU who had solved the questions earlier.[5] We define *competitiveness* as a dummy that takes a value 1 if the subject chose the tournament compensation scheme and 0 if the subject chose the piece-rate compensation scheme. We define *confidence* as a dummy that takes a value 1 if the subject believes that her performance in the actual task will exceed those of others in the same session, 0 otherwise.

Second, to measure risk preferences, we used the investment game of Gneezy and Potters (1997). In this, subjects allocated a portion of their endowment (Rs. 150) to a risky lottery and set aside the remainder. If they won the lottery based on a roll of a dice, the invested amount would be tripled and they would also get any amount they set aside. Conversely, if they lost the lottery, they would only receive the amount that was set aside. We define *investment* as the proportion allocated to the risky lottery in the investment game.

In the second part of the study, we implemented a socioeconomic survey that collected details on family background characteristics, school and college information, academic performance, aspirations, and details on participation in extra-curricular activities. To measure cognitive outcomes, we collected data on scores on semester-wise university examinations. To measure personality traits, we administered the 10-item Big-Five inventory (Gosling et al., 2003). The five traits in the Big Five are defined as follows. *Openness to experience* is the tendency to be open to new aesthetic, cultural, or intellectual experiences. *Conscientiousness* refers to a tendency to be organized, responsible, and hard working. *Extraversion* relates to an outward orientation rather than being reserved. *Agreeableness* is related to the tendency to act in a cooperative and unselfish manner. *Neuroticism* (opposite of *Emotional stability*) is the tendency to experience unpleasant emotions easily, such as anger, anxiety, depression, or vulnerability.

Overall, we conducted 60 sessions with 2065 subjects, resulting in approximately 34 subjects per session. Each session lasted about 75 minutes. All subjects received a

[5] Following Bartling et al. (2009), we implemented a pilot version of this game where 40 students from DU had participated in this game. We use the performance of these students for comparison in the tournament wage scheme.

show-up fee of Rs. 150. Further, in each session, 20 percent of the subjects were randomly chosen to be paid for their decisions on one of the randomly chosen tasks from the experiment module. The average additional payment was Rs. 230. All subjects participated only once in the study.

3. Empirical Specification

For the purpose of this analysis, we exclude all those students who were not admitted on the basis of discipline-specific cutoffs. This includes students belonging to disadvantaged backgrounds (Scheduled Castes, Scheduled Tribes and Other Backward Castes) for whom affirmative action policies mandate a fixed number of seats; students admitted on the basis of excellence in sports or other extra-curricular activities, those who transferred from one college to another after enrollment or switched disciplines within a college; and those providing insufficient identification information.[6] This reduces our sample to 1329 subjects. We follow the procedure outlined in Pop-Eleches and Urquiola (2013) to construct our final sample from the pool of 1329 eligible subjects. We use admission cutoffs as exogenously announced by the individual colleges as our criteria to sort the 15 colleges in our sample into the following four categories such that the group of colleges that belong to the higher categories have consistently higher admission cutoffs than the cutoffs of the groups of colleges that belong to the lower categories. The 15 colleges in our sample are consequently given four ranks ranging from 1 (lowest rank) to 4 (highest rank). Since cutoffs also vary by discipline (commerce and economics), combination of subjects in high school, gender and year, for each rank, we use three sets of cutoffs for our four ranks, where each rank (and colleges therein) receives a cutoff equal to the lowest admission cutoff released by the higher ranked college in that category. Note that in each rank, the cutoffs also vary by discipline, gender, and year. So the rank 4 colleges receive a cutoff equal to the lowest admission cutoff released by this group of colleges and results in an RD sample where colleges in rank 4 are assigned to the treatment (better quality college) and the remaining colleges (in ranks 3, 2, and 1) are assigned to be the control (lower quality college). Next, colleges in ranks 3

[6] Of 2065 students in our sample, 29 percent are affirmative action beneficiaries, 4.8 percent got admitted on the basis of sports and other activities, 0.6 percent migrated within or across colleges and 1.4 percent provided insufficient information.

and 4 would receive a cutoff equal to the lowest admission cutoff released by this group of colleges and results in an RD sample where colleges ranked 3 and 4 are assigned to the treatment and the remaining colleges (ranks 2 and 1) are assigned to the control. Finally, a third sample is constructed where colleges ranked 4, 3, and 2 receive a cutoff equal to the lowest admission cutoff released by this group of colleges and results in an RD sample where these colleges are assigned to the treatment group and colleges in rank 1 are assigned to the control. We finally "stack" all three sets of between college rank cutoffs that also vary by discipline, gender, and year to create our final analysis sample that now includes 3656 subjects.

We estimate the following "intent-to-treat" type OLS regression model using a RD approach:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 d_i + \beta_3 d_i^2 + \beta_4 d_i T_i + \beta_5 d_i^2 T_i + \sum_{\mathrm{j=6}}^{\mathrm{k}} \beta_j \mathrm{X_{ij}} + \varepsilon_i \qquad (1)$$

Where Y_i is the outcome variable, d_i is the running variable computed as the difference between student i's average class 12 examination score and the relevant college rank-discipline-year specific cutoff, T_i takes a value 1 if d_i is non-negative and 0 otherwise. We control for the running variable to account for selection on observables (Heckman and Robb, 1985). Further, we also allow for a quadratic specification in the running variable to allow for non-linearity in the relationship between the outcome and the running variable.[7] We also include a vector of controls/pre-determined characteristics (Xs) such as mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion to improve the precision of our estimates. Finally, ε_i is the iid error term. All regression estimates are clustered at the session level. In this specification, β_1 captures the intent-to-treat effect or the effect of being eligible to enroll in a better quality college or exposure to better quality peers at the cutoff.

Note, not all students eligible to enroll in the better quality college (treatment) will take admission in that college. Similarly, some students assigned to the low quality

[7] In the robustness section, we also present the effects using alternative parametric models. Overall, we do not find our results susceptible to the parameterization of the control function, the sample size and or the estimation technique employed (OLS, IV).

colleges might seek admission into the higher quality college through personal connections with the principal, for instance.[8] Imperfect compliance entails the application of a "fuzzy" RD design (Hahn, Todd and Van der Klaauw 2001; Lee and Lemieux 2010) where the treated (TR_i), i.e., enrolled in a better quality college will be instrumented by the discontinuity in the running variable. The corresponding first-stage regression would be:

$$TR_i = \alpha_0 + \alpha_1 T_i + \alpha_2 d_i + \alpha_3 d_i^2 + \alpha_4 d_i T_i + \alpha_5 d_i^2 T_i + \sum_{\mathrm{j}=6}^{\mathrm{k}} \alpha_j \mathrm{X_{ij}} + \eta_i \tag{2}$$

and the corresponding second-stage regression would be:

$$Y_i = \delta_0 + \delta_1 TR_i + \delta_2 d_i + \delta_3 d_i^2 + \delta_4 d_i T_i + \delta_5 d_i^2 T_i + \sum_{\mathrm{j}=6}^{\mathrm{k}} \alpha_j \mathrm{X_{ij}} + \mu_i \tag{3}$$

Where the coefficient estimate on *TR* gives us the local average treatment effect (LATE) from being enrolled in a better quality college, computed as the ratio of the reduced form coefficients ($\delta_1 = \beta_1 / \alpha_1$) as long as we use the same bandwidth and polynomial order as in equations (1) - (3).

3.1 Testing the validity of the RD design

The "fuzzy" RD model relies on two assumptions: (a) there is no manipulation of the assignment variable at the cutoff, and (b) the probability of being enrolled in a better quality college is discontinuous at the cutoff. This is also proof of a strong first-stage regression, necessary for obtaining a valid second stage estimate.

The estimation strategy would result in biased estimates if students could perfectly control the side of the cutoff they will fall under. However, as we argue below, this is not possible under the admission process in DU. First, the scoring of the class 12 examinations is double blind, making manipulation of the scores difficult, if not outright impossible. Second, at the time of application to DU colleges, students do not know what the various cutoffs will be for that year.[9] Moreover, since the rule for

[8] In our sample, only 0.67 percent of the subjects who have a negative distance from the cutoff are enrolled in a higher ranked college and approximately 12 percent of the subjects who have a positive distance from the cutoff are enrolled in a lower ranked college.

[9] Based on historical trends, students may have a rough sense of the range of the cutoff, but this does not invalidate our analysis.

determining these cutoffs is never public knowledge, students cannot perfectly predict future cutoffs. Overall, it is virtually impossible for students to perfectly manipulate either the class 12 examination scores or the side of the college cutoff they will ultimately fall on.

As colleges are required to simultaneously reduce cutoffs till there are no vacancies, it is very unlikely that students just above the cutoff differ systematically from those just below the cutoff on unobservables. We can, however, check for discontinuities in other predetermined characteristics. To do this, we collected information on family background characteristics such as mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. In Table 1 we formally test for discontinuity in each of these covariates by estimating equation (1) with the predetermined family background characteristics as the dependent variables. Since our main impact estimates are presented for the pooled sample, and separately by gender, we examine the validity of the RD design in Table 1 separately for the pooled sample (Panel A), males (Panel B), and females (Panel C). We find that the impact of the treatment indicator on the predetermined variables is mostly small and never significantly different from zero, confirming the validity of the RD design.

In Table 2 below, we present estimates from equation (2). We find that students who are eligible to enroll in a better quality college are 75 percent more likely to do so. We find similar strong effects of the eligibility to enroll in a better quality college for both males and females. We find that the admission rules used in DU are therefore strong with some imperfect compliance making the fuzzy RD design appropriate to follow. The results from the corresponding IV specification are presented in the Robustness section. We also present the first-stage relationship between enrollment in a better quality college and the running variable for the pooled sample, males, and females in Figure 2. We see a clear jump in the probability of enrolling in a better quality college at the cutoff for all three samples in Figure 2.

4. Results

Our primary results focus on the impact of being eligible to enroll in a better quality college, that is, intent-to-treat effects. The impact of enrollment in a better quality college, that is, the impact of the treatment on the treated is presented in Section 5 below.

4.1 Summary Statistics

In Table 3, we present descriptive statistics for our sample. In Panel A, we summarize average performance on semester-wise university wide examinations – our measures of cognitive skills accumulated during college.[10] The curriculum and examinations are identical for all students within a discipline across all colleges in DU and grading of the examinations is double blind. Note that this a novel point about the data as firstly, in most other papers in the literature, curriculum and examinations vary across treatment and control schools or colleges; secondly, while they typically have information on only the exit examination scores, we are able to observe students' scores in multiple semesters. We find that students' performance on the university wide semester examinations improves with time – closer to graduation. This is not surprising as students get closer to graduation, they have fewer chances left for improving their overall performance and as a result, are likely to put in more effort.

In Panel B, we summarize average choices on the behavioral preferences: competitiveness, confidence, and investment. In our sample, 31 percent of the subjects choose the tournament payment scheme (indicator of competitive behavior) and 44 percent of the subjects are confident. These findings are in line with other papers in the literature that find that about one-third of subjects choose the tournament wage scheme and subjects often irrationally overestimate their own abilities across tasks (e.g., Niederle and Vesterlund, 2007; Camerer and Lovallo, 1999; Merkle and Weber, 2011; Dasgupta et al., 2015). Finally, the average investment of 47 percent in the risky asset, our measure of risk preference is in the range of 44.67-70.86 percent for student populations mostly in developed countries (Charness and Viceisza, 2015).

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[10] An academic year has 2 semesters with exams held in December and May. Since, our study was conducted during January-March, for 2nd and 3rd year students, we have exam scores for 3 semesters and 5 semesters respectively.

In Panel C, we summarize subjects' personality traits: agreeableness, emotional stability, conscientiousness, openness to experience, and extraversion. In our sample, subjects report a higher score on agreeableness, conscientiousness, and openness to experience than they do for extraversion and emotional stability. This trend is in line with Mueller and Plug (2006) who also find a similar ordinal ranking.

4.2 Intent-to-treat effects: Cognitive outcomes, Behavioral outcomes, and Personality traits

In each of the tables below, we present the impact of being eligible to enroll in a better quality college on cognitive, behavioral, personality outcomes for three samples: pooled (Panel A), males (Panel B), and females (Panel C). Since the effects of peer environment could manifest differently among males and females, we report our results by gender.

We present the results from equation (1) using scores on the standardized university level semester examinations I-V as the dependent variable in columns 2-6 in Table 4 and the average score over semesters I-V are reported in column 1, Table 4. We find that enrolling in a better quality college does not improve the test scores in semester I-III, but it does have a statistically significant impact on scores in semesters IV and V. This suggests that it takes time to build friendships, become accustomed to one's peers, and form study groups that would then lead to generation of knowledge spillovers, thereby having an impact on one's test scores as observed in semesters IV and V. We find that the opportunity to enroll in a better quality college increases test scores in semesters IV and V by 3 and 5 percentage points respectively. These translate to roughly 0.25 and 0.55 standard deviation improvements in test scores during semesters IV and V. Most students graduate after Semester VI so this indicates that with time, exposure to more able peers can influence one's cognitive outcomes. Our positive findings on exam scores are in line with other literature from developed countries where authors find a positive impact of enrollment in elite colleges on graduation rates (Long, 2008; Saavedra, 2009).

Upon further examining these effects by gender, we find that it is females who benefit from the exposure to better peers, and these effects peter out over time.

Our findings suggest that students just above the cutoff (are students with relatively low-ability when compared to their peers) benefit from being exposed to their higher ability peers compared to students just below the cutoff (who are of high-ability compared to their peers in the lower quality college). Our main result is consistent with Jain and Kapoor (2015) who find that it is low-ability students when randomly assigned to high-ability peers that benefit compared to high-ability students using data on students' academic performance in a prestigious business school in India.

The second set of results concern behavioral outcomes – competitiveness, confidence, and investment. The ITT effects for these traits are shown in Table 5 below. While in the pooled sample and among males, we do not find any significant effects, we find that females differ significantly in their risk preferences. Our results indicate that women who are eligible to enroll in better quality college invest almost 7 percentage points more in the investment game, therefore being less risk-averse than their female counterparts not eligible to enroll in the better quality college. To the extent that females are more risk-averse than males and this gender gap in risk preferences has implications for selecting into competitive environments and occupational choice, this result suggests that higher quality colleges may result in a narrowing of this gender gap.

The last set of impact estimates pertains to personality outcomes – Big Five traits of openness to experience, conscientiousness, extraversion, agreeableness and emotional stability (Table 6). We find no impact of eligibility to enroll in a higher quality college on most Big Five traits except openness to experience that reduces by 0.21 standard deviations. Further upon splitting the data by gender, we find that this decline in openness to experience occurs only for males (by 0.365 standard deviations). Overall, our results suggest that knowledge is more transferable and hence can influence examination scores more easily than personality traits that are less malleable through the channel of ‘direct tutoring’.

We explore the potential pathways for these gender differential results in Table 10 and find higher attendance rates among females to be one of the likely channels explaining the gender differences in returns to better peer environment.

5. Robustness

We show here that the intent-to-treat effects reported earlier in Tables 4-6 are robust to a number of econometric concerns such as: choice of the polynomial order, bandwidth selection, estimation technique, and measurement error around the cutoff. Robustness results are presented for pooled sample, males and females in Tables 7-9.

First, to check for specification bias arising from the choice of second order polynomial, we present the impact of eligibility to enroll in a better quality college on all outcomes using a flexible cubic polynomial and find that the results remain largely similar to the ones presented earlier in Tables 4-6.

Second, we also present the estimates from the IV strategy described previously in Section 3. We find that our IV or LATE results are consistently higher than the OLS estimates reported in Tables 4-6.

Third, we restrict our data to the optimal bandwidth prescribed by Calonico, Cattaneo and Titiunik (2014) and find our results to be robust to the width of the window around the cutoff.

Finally, it has been argued that if there is manipulation, it is likely to occur right around the cutoff. One way to check if the results are robust to such possible behavior is to discard the observations near the cutoff and re-estimate the model (Barreca et al., 2011; Filmer and Schady, 2014). We report results from these “donut” regressions where we exclude all observations within (-0.5, 0.5) window around the cutoff and re-estimate equation (1) and once again, find that our primary results continue to hold.

6. Discussion and Conclusion

To the best of our knowledge, this is the first paper in the literature that goes beyond previously examined cognitive outcomes to causally identify the effects of exposure to better peers - as captured by college selectivity - on cognitive, behavioral, and personality outcomes. We exploit the variation in college admission cutoffs along and compare students just above the cutoff with those just below the cutoff to determine the impact of the eligibility to enroll in a better quality college, where they are exposed to relatively high-achieving peers, on these outcomes.

Using data from 2nd and 3rd year college students enrolled in commerce and economics disciplines, our results indicate that the exposure to a superior peer environment improves scores on standardized semester exams, particularly for females. In terms of behavioral and personality traits, we find that females with access to better quality colleges are less risk-averse, while males in these colleges are less likely to be open to experiences. However, we do not observe significant effects on other traits.

While we are able to estimate the returns to college quality for a range of new outcomes considered important in the literature, it should be noted that we are not able to examine these effects for the entire population of DU students. Also, since DU is one of the premier universities in India, its students are not representative of the average Indian college student. Our results must be assessed keeping these limitations in mind.

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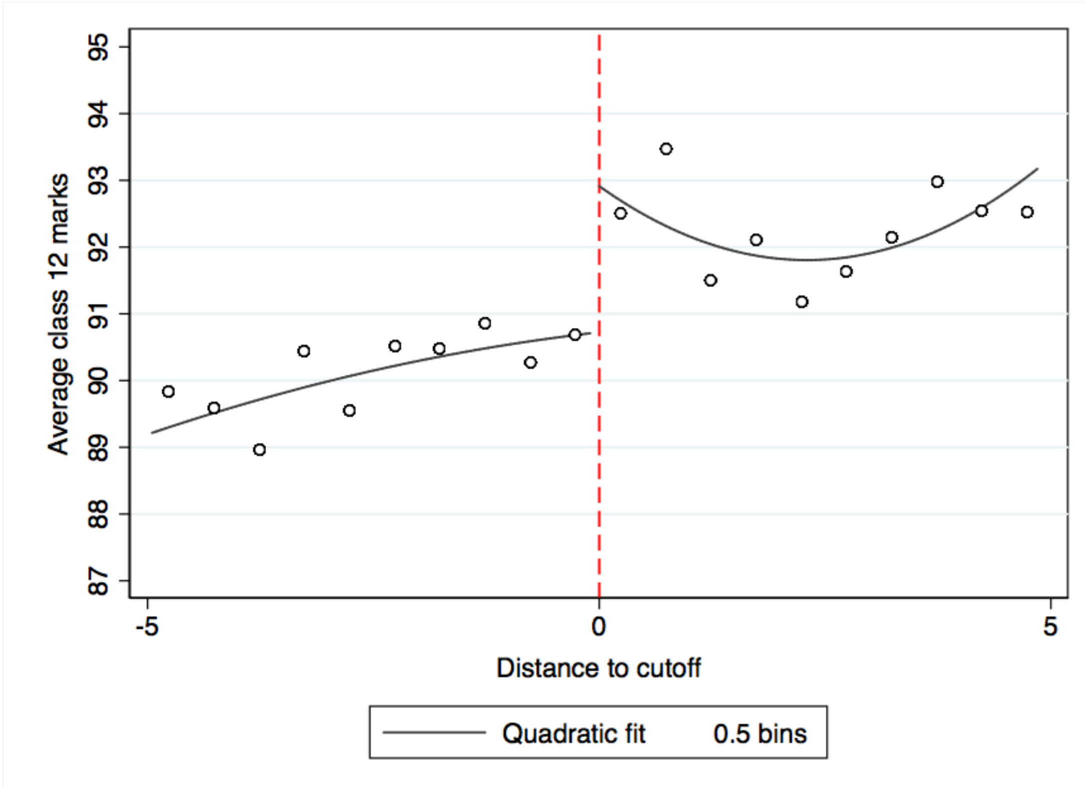

Figure 1: Difference in Peer Quality

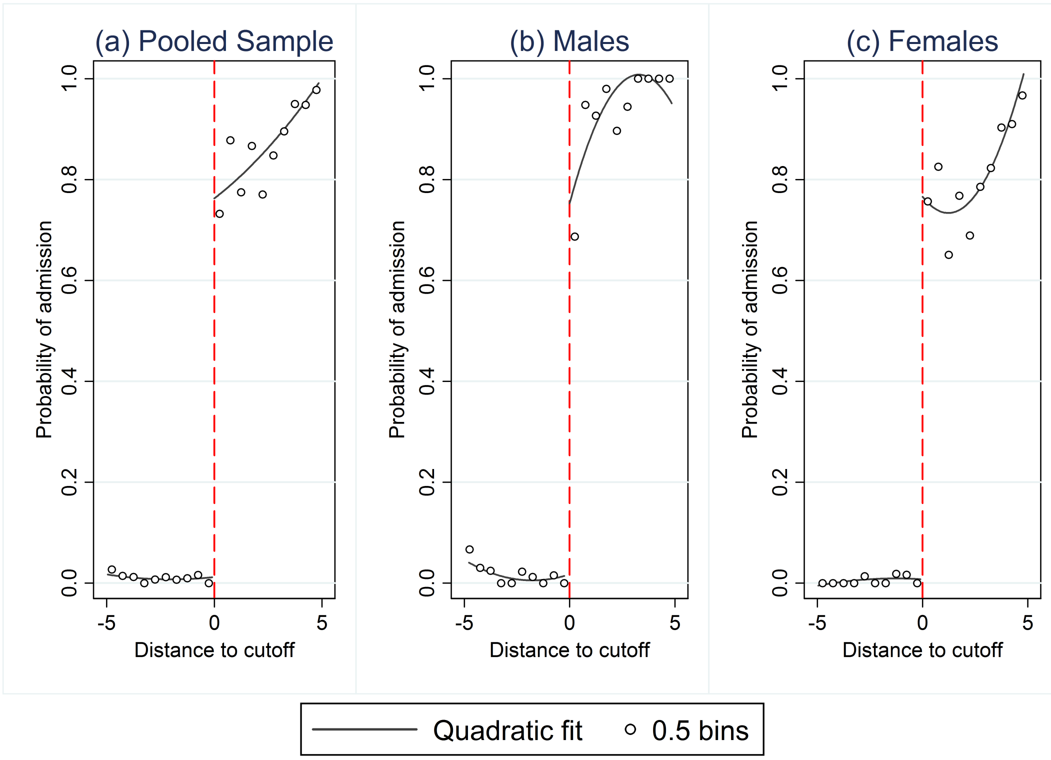

Figure 2: First Stage Relationship

Table 1: Balance in Baseline Covariates

	Age	Mother's education	Father's education	No. of Siblings	Hindu	Private School	Family Income
Panel A: Full Sample							
1(Above cutoff)	0.036	0.034	-0.033	-0.016	-0.035	0.038	0.023
	(0.101)	(0.053)	(0.051)	(0.119)	(0.031)	(0.051)	(0.070)
Observations	2352	2377	2377	2377	2377	2377	2377
Panel B: Males							
1(Above Cutoff)	0.025	-0.035	-0.079	-0.198	-0.030	0.009	0.081
	(0.200)	(0.096)	(0.097)	(0.210)	(0.050)	(0.083)	(0.096)
Observations	1037	1053	1053	1053	1053	1053	1053
Panel C: Females							
1(Above cutoff)	0.088	0.083	-0.013	0.122	-0.054	0.057	-0.043
	(0.095)	(0.076)	(0.061)	(0.114)	(0.043)	(0.062)	(0.088)
Observations	1315	1324	1324	1324	1324	1324	1324

Notes: This table reports the reduced form estimates using the flexible second order polynomial described in equation (1). All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise.

Table 2: First Stage Discontinuity

	Full Sample	Males	Females
Without controls	0.748***	0.730***	0.758***
	(0.057)	(0.063)	(0.074)
With controls	0.747***	0.733***	0.762***
	(0.055)	(0.063)	(0.071)
Observations	2352	1037	1315

Notes: This table shows the first stage discontinuity results using a flexible second order polynomial described in the text. Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 3: Summary Statistics

Variables	Mean (std. dev) (1)
Panel A: Cognitive outcomes	
Average score on semesters 1-V examinations	70.45
	(7.40)
Scores on semester I examination	69.69
	(9.63)
Scores on semester II examination	69.24
	(8.56)
Scores on semester III examination	69.03
	(8.74)
Scores on semester IV examination	72.05
	(8.11)
Scores on semester V examination	75.23
	(9.20)
Panel B: Behavioral traits/preferences	
Competitiveness (=1 if tournament wage scheme is chosen, 0 if piece-rate wage scheme)	31.09 (46.29)
Confidence (=1 if the subject believes that her performance in the actual task will exceed those of others in the same session, 0 otherwise)	44.21 (49.67)
Risk preference (proportion allocated to the risky option)	46.60
	(19.13)
Panel C: Personality traits	
Extraversion z-score	0.0034
	(0.99)
Conscientiousness z-score	0.017
	(0.97)
Agreeableness z-score	0.11
	(0.92)
Emotional stability z-score	-0.06
	(0.99)
Openness to experience z-score	0.0004
	(0.96)
Panel D: Socioeconomic characteristics	
Age (in years)	19.66

	(0.86)
Male (=1 if male, 0 if female) (in %)	44.13
	(49.66)
Hindu (=1 if religious category is Hindu, 0 otherwise) (in %)	92.13
	(26.93)
Number of siblings	1.35
	(0.72)
Private school (=1 if graduated high school from a private school, 0 otherwise) (in %)	84.81
	(35.89)
Mother's education (=1 if mother has an undergraduate and or higher degree, 0 otherwise) (in %)	75.30
	(43.13)
Father's education (=1 if father has an undergraduate and or higher degree, 0 otherwise) (in %)	78.20
	(41.29)
Income (=1 if monthly family income <=50,000 Rupee, 0 otherwise) (in %)	30.54
	(46.06)

Notes: Standard deviations are reported in parenthesis. All measures reported in z-scores are standardized using the mean and standard deviation of the control group/lower quality college as the reference category. Sample restricted to +/- 5 window.

Table 4: ITT effects: Cognitive outcomes

	Av. score	Sem. I	Sem. II	Sem. III	Sem. IV	Sem. V
Panel A: Full Sample						
1(Above Cutoff)	2.017	2.678	1.909	1.598	2.819*	4.838*
	(1.622)	(1.955)	(1.694)	(1.569)	(1.542)	(2.509)
Observations	2330	2317	2312	2302	1082	1078
Panel B: Males						
1(Above Cutoff)	-0.436	-1.001	-1.081	-0.965	3.505*	4.573
	(1.776)	(2.488)	(2.062)	(1.954)	(1.793)	(2.930)
Observations	1024	1024	1021	1016	447	446
Panel C: Females						
1(Above Cutoff)	3.254*	5.259***	3.694**	3.134*	1.945	4.125
	(1.703)	(1.823)	(1.830)	(1.792)	(1.696)	(2.465)
Observations	1306	1293	1291	1286	635	632

Notes: This table shows the reduced form effect on semester scores using a flexible second order polynomial described in equation (1). Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 5: ITT effects: Behavioral outcomes

	Competition	Confidence	Investment
Panel A: Full Sample			
1(Above Cutoff)	0.059	-0.061	2.114
	(0.064)	(0.063)	(2.210)
Observations	2349	2352	2343
Panel B: Males			
1(Above Cutoff)	0.082	0.080	-1.965
	(0.086)	(0.101)	(4.216)
Observations	1037	1037	1032
Panel C: Females			
1(Above Cutoff)	0.100	-0.087	7.748***
	(0.072)	(0.077)	(2.691)
Observations	1312	1315	1311

Notes: This table shows the reduced form effect on behavioral outcomes using a flexible second order polynomial described in equation (1). Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 6: ITT effects: Personality Traits

	Big Five				
	Extraversion	**Agreeableness**	**Conscientiousness**	**Emotional Stability**	**Openness to experience**
Panel A: Full Sample					
1(Above Cutoff)	-0.166	0.162	-0.103	0.012	-0.220*
	(0.123)	(0.103)	(0.128)	(0.108)	(0.114)
Observations	2315	2302	2324	2313	2312
Panel B: Males					
1(Above Cutoff)	-0.181	0.116	-0.271	0.064	-0.372**
	(0.174)	(0.218)	(0.172)	(0.169)	(0.186)
Observations	1015	1007	1023	1012	1012
Panel C: Females					
1(Above Cutoff)	-0.159	0.124	0.053	-0.050	-0.049
	(0.175)	(0.111)	(0.196)	(0.174)	(0.147)
Observations	1300	1295	1301	1301	1300

Notes: This table shows the reduced form effect on personality traits using a flexible second order polynomial described in equation (1). Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. 1(Above Cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 7: Robustness Checks: Cognitive Outcomes

	Av. score	Sem. I	Sem. II	Sem. III	Sem. IV	Sem. V
Panel A: Full Sample						
Without controls	2.097	2.759	1.973	1.521	3.056*	5.094*
	(1.662)	(1.973)	(1.715)	(1.611)	(1.587)	(2.648)
Cubic	2.591	2.723	2.600	2.124	3.300	5.025*
	(2.054)	(2.422)	(2.121)	(2.029)	(2.542)	(2.808)
IV	2.792	3.942	2.660	2.022	3.812**	6.732
	(2.132)	(2.568)	(2.187)	(1.962)	(1.880)	(4.190)
CCT Bandwidth	2.378	2.951	2.066	1.364	2.883*	5.225*
	(1.702)	(1.858)	(1.900)	(1.749)	(1.503)	(2.588)
Donut	3.342	4.340	3.143	2.355	5.026**	6.245**
	(2.017)	(2.626)	(2.241)	(2.004)	(1.898)	(2.947)
Panel B: Males						
Without controls	0.086	-0.293	-0.565	-0.732	3.845**	5.660
	(1.794)	(2.503)	(1.972)	(1.920)	(1.749)	(3.955)
Cubic	0.005	-0.430	-0.026	0.127	3.350	5.111
	(2.212)	(3.009)	(2.607)	(2.413)	(3.167)	(3.778)
IV	0.239	0.086	-0.546	-0.519	5.141**	7.937
	(2.530)	(3.552)	(2.770)	(2.638)	(2.406)	(6.726)
CCT Bandwidth	0.341	0.025	0.140	-0.279	3.576*	4.093
	(1.634)	(2.990)	(2.490)	(2.224)	(1.806)	(2.614)
Donut	1.406	0.461	0.329	-0.270	5.853**	5.979
	(2.203)	(3.430)	(2.654)	(2.429)	(2.387)	(3.919)
Panel C: Females						
Without controls	3.168*	5.190***	3.389*	2.864	2.312	4.404*
	(1.724)	(1.841)	(1.857)	(1.817)	(1.811)	(2.424)
Cubic	4.328*	5.512**	4.480**	3.517	3.330	4.184
	(2.227)	(2.500)	(2.209)	(2.363)	(2.573)	(2.659)
IV	3.601*	5.950***	4.172*	3.235	2.199	3.682
	(2.113)	(2.130)	(2.243)	(2.206)	(2.273)	(3.326)
CCT Bandwidth	3.304*	5.013***	3.978**	3.600*	1.701	4.881*
	(1.722)	(1.790)	(1.911)	(1.887)	(1.629)	(2.529)
Donut	4.291*	6.951**	4.974**	4.052*	3.475	5.252*
	(2.246)	(2.611)	(2.472)	(2.287)	(2.545)	(3.005)

Notes: This table shows robustness checks for the effect on semester scores. All regressions include course and year fixed effects. Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. CCT bandwidth refers to the optimal bandwidth detailed in Calonico, Cattaneo and Titiunik (2014). The donut results exclude all observations within 0.5 window around the cutoff. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 8: Robustness Checks: Behavioral Outcomes

	Competition	Confidence	Investment
Panel A: Full Sample			
Without controls	0.058	-0.072	1.364
	(0.063)	(0.063)	(2.302)
Cubic	0.078	0.064	0.119
	(0.087)	(0.073)	(3.546)
IV	0.090	-0.084	3.386
	(0.086)	(0.087)	(3.123)
CCT Bandwidth	0.063	-0.073	1.907
	(0.069)	(0.064)	(2.207)
Donut	0.184**	-0.175*	4.965*
	(0.084)	(0.097)	(2.968)
Panel B: Males			
Without controls	0.083	0.060	-2.732
	(0.084)	(0.102)	(4.140)
Cubic	0.042	0.157	-3.622
	(0.117)	(0.130)	(6.206)
IV	0.162	0.074	-2.217
	(0.120)	(0.142)	(5.862)
CCT Bandwidth	0.080	0.061	0.077
	(0.087)	(0.115)	(3.309)
Donut	0.269	-0.060	1.118
	(0.147)	(0.154)	(5.825)
Panel C: Females			
Without controls	0.094	-0.104	7.364***
	(0.072)	(0.075)	(2.681)
Cubic	0.130	0.024	5.472
	(0.115)	(0.105)	(3.405)
IV	0.081	-0.149	9.559***
	(0.093)	(0.099)	(3.558)
CCT Bandwidth	0.093	-0.010	6.864**
	(0.073)	(0.088)	(2.656)
Donut	0.155	-0.205	8.885**
	(0.083)	(0.101)	(3.468)

Notes: This table shows robustness checks for the effect on behavioral outcomes. All regressions include course and year fixed effects. Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. CCT bandwidth refers to the optimal bandwidth detailed in Calonico, Cattaneo and Titiunik (2014). The donut results exclude all observations within 0.5 window around the cutoff. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 9: Robustness Checks: Personality Traits

	Big Five				
	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness to experience
Panel A: Full Sample					
Without controls	-0.161	0.147	-0.080	-0.018	-0.212*
	(0.120)	(0.106)	(0.132)	(0.112)	(0.107)
Cubic	-0.200	0.061	-0.176	0.074	0.012
	(0.201)	(0.174)	(0.208)	(0.138)	(0.167)
IV	-0.189	0.260*	-0.218	-0.049	-0.201
	(0.160)	(0.138)	(0.169)	(0.160)	(0.143)
CCT Bandwidth	-0.063	0.153	-0.046	0.004	-0.220*
	(0.110)	(0.100)	(0.115)	(0.095)	(0.114)
Donut	-0.239	0.227	-0.207	-0.004	-0.285*
	(0.166)	(0.140)	(0.151)	(0.170)	(0.163)
Panel B: Males					
Without controls	-0.174	0.109	-0.231	0.000	-0.358*
	(0.174)	(0.214)	(0.186)	(0.191)	(0.179)
Cubic	-0.343	-0.105	-0.184	0.097	-0.323
	(0.245)	(0.279)	(0.306)	(0.246)	(0.274)
IV	-0.228	0.252	-0.477**	0.044	-0.437**
	(0.224)	(0.287)	(0.220)	(0.270)	(0.220)
CCT Bandwidth	-0.269	0.077	-0.147	0.068	-0.431**
	(0.201)	(0.170)	(0.166)	(0.131)	(0.193)
Donut	-0.627**	0.403	-0.469**	0.075	-0.356
	(0.256)	(0.298)	(0.229)	(0.239)	(0.265)
Panel C: Females					
Without controls	-0.142	0.095	0.027	-0.079	-0.045
	(0.171)	(0.117)	(0.196)	(0.172)	(0.149)
Cubic	-0.043	0.087	-0.075	0.043	0.395*
	(0.280)	(0.209)	(0.318)	(0.247)	(0.217)
IV	-0.219	0.147	-0.009	-0.028	0.015
	(0.246)	(0.152)	(0.252)	(0.232)	(0.200)
CCT Bandwidth	-0.039	0.089	0.004	-0.056	0.061
	(0.144)	(0.113)	(0.202)	(0.145)	(0.131)
Donut	0.080	0.079	-0.004	-0.119	-0.218
	(0.185)	(0.159)	(0.221)	(0.229)	(0.166)

Notes: This table shows robustness checks for the effect on personality traits. All regressions include course and year fixed effects. Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. CCT bandwidth refers to the optimal bandwidth detailed in Calonico, Cattaneo and Titiunik (2014). The donut results exclude all observations within 0.5 window around the cutoff. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 10: Pathways

	Males		Females	
	Attendance	**External Tutorial**	**Attendance**	**External Tutorial**
1(Above Cutoff)	-0.098	0.010	0.223**	-0.036
	(0.084)	(0.124)	(0.087)	(0.085)
Observations	1037	1037	1315	1315

Notes: Controls include mother's education, father's education, number of siblings, private school enrollment, age, family income, and religion. All regressions include course and year fixed effects. Standard errors clustered at the session level are reported in parentheses. 1(Above cutoff) takes a value 1 if distance from the cutoff is non-negative, 0 otherwise * significant at 10%,** significant at 5%,*** significant at 1%.

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