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Cognitive, socioemotional, and behavioural returns to college quality

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Abstract: We exploit the variation in the admissions process across colleges of a leading Indian university to estimate the causal effects of enrolling in a selective college on: cognitive attainment using scores on standardized university exams; behavioural preferences such as risk, competitiveness, and overconfidence; and socioemotional traits using measures of Big Five personality. Using a regression discontinuity design, we find that enrolling in a selective college leads to improvements in females' exam scores with no effect on males' scores. Marginally admitted females in selective colleges become less overconfident and less risk averse as compared to their counterparts in the less selective colleges. Males in selective colleges experience a decline in extraversion and conscientiousness. We find higher attendance rates among females to be one of the likely channels explaining the gender differences in returns to better college and peer environment. To the best of our knowledge, this is the first paper in the literature to go beyond cognitive outcomes, to causally identify the returns to college quality on both behavioural and socioemotional traits.

Keywords: cognitive attainment, behaviour, personality, college quality, peer effects, India
JEL classification: I23, C9, C14, J24, O15

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1 Introduction

Cognitive ability, completed years of schooling, and test scores have long been considered important determinants of life success (e.g., Hanushek and Woessmann, 2008; Oreopoulos and Salvanes, 2011). However, there is now increasing evidence that suggests behavioral preferences and socioemotional traits like self-control, appetite for risk taking, and competitiveness to be equally important in determining educational attainment, occupational choice, labor market performance, and overall well-being (e.g., Almas et al., 2016; Almlund et al., 2011; Borghans et al., 2008; Heckman et al., 2006).

College is an important milestone of life that is believed to develop several aspects of an individual's human capital, broadly defined to include both cognitive and socioemotional traits. Consequently, there is great emphasis on enrolling in selective colleges that are expected to provide more competitive and able peer environments, more qualified teachers, better role models embodied in their alumni, greater access to extra-curricular activities, and serve as a signal for higher ability. Experiencing an environment such as this for 3-4 years is likely to shape one's broader skill set. While the existing literature on school and college quality has explored mainly academic outcomes and reports positive or insignificant effects of exposure to elite educational institutions (Abdulkadiroğlu et al., 2014; Ajayi, 2014; Jackson, 2010; Lucas and Mbiti, 2014; Pop-Eleches and Urquiola, 2013; Rubinstein and Sekhri, 2013; Saavedra 2009), it remains largely silent on the accompanying behavioral responses, and underlying mechanisms that may explain these mixed results.[1]

The objective of this paper is to examine the returns to exposure to a selective college on not just academic outcomes, but also on measures of risk taking, competitiveness, overconfidence, and Big Five personality traits.[2] To the best of our knowledge, this is the first paper in the literature to causally identify the effects of college environment on socioemotional and behavioral aspects of human capital accumulation. In doing so, we use rich student-level data in a regression discontinuity design to address the selection problem arising from sorting, i.e. high-achieving students self-select into higher quality colleges while low-achieving students

[1] There are some exceptions. For instance, Pop-Eleches and Urquiola (2013) comment on the behavioral responses to attending elite schools. Murphy and Weinhardt (2016) and Elsner and Isphording (2016a) attribute the better academic performance of high-ranking school students to confidence and optimism respectively.

[2] That personality is malleable in adolescence and young adulthood is now accepted in the psychology and economics literature (e.g., Borghans et al., 2008; Specht et al., 2011). While cognitive ability, typically measured by IQ, is relatively stable after age 10, there is increasing evidence that both negative and positive experiences can impact how behavior and personality is expressed (e.g., Chuang and Schechter, 2015; Schurer et al., 2015).

sort into lower quality colleges.

We analyze data from the University of Delhi (DU), one of the top public universities in India, to estimate the returns to college quality across a range of colleges with varying levels of selectivity that are all within the same educational context. Admission into colleges within the DU system is based on the incoming cohorts' average scores on high school exit examinations. This gives rise to college-discipline-specific admission cutoffs that determine an individual's eligibility to enroll in a specific discipline in a college. We exploit students' inability to manipulate this admission cutoff and compare outcomes of students just above the cutoff to those just below the cutoff to estimate the causal impact of exposure to selective colleges.

Value-added models of learning will predict better academic and non-academic outcomes for students just above the cutoff enrolled in the more selective colleges. Being in the company of smarter peers can allow richer learning opportunities, provide a more dynamic environment for group interactions, and serve as a motivation to work harder to keep up with the competition (e.g., Jain and Kapoor, 2015; Feld and Zölitz, 2017). However, in being the marginal student, those just above the cutoff are also the worst-off relative to their peer group ('small fish in a big pond') while those just below the cutoff are relatively better than their peers ('big fish in a small pond'). The marginally admitted student has a lower relative rank among her peer group that could lower her 'academic self-concept' resulting in a detrimental or zero impact on not just her future academic performance but also her behavior and personality (Marsh et al., 2008). Using panel data from the UK, Murphy and Weinhardt (2016) find that students with the same ability but higher relative rank, due to idiosyncratic variation in cohort composition in primary school, perform significantly better in secondary school. Applying a similar identification strategy to the National Longitudinal Study of Adolescent Health data from the US, Elsner and Isphording (2016a) find that students with higher ordinal rank are more likely to complete high school, and enter and graduate from college. In the same context, Elsner and Isphording (2016b) also find that low relative rank increases the likelihood of smoking, drinking, and engaging in violent behavior, and they attribute this to diminished future expectations and perceived status arising from lower ordinal rank. Students above the cutoff face tradeoffs between the positive effects of higher ability peer environments and negative effects of low relative rank (Cicala et al., 2016). Consequently, the net effects of enrolling in a more selective college could go in either direction.[3]

We combine data from a series of unique incentivized tasks and socioeconomic surveys administered to over 2000 undergraduate students at different colleges of DU to examine the returns to enrollment in more selective college environments. The first outcome of interest is academic attainment as measured by scores on standardized university-level examinations. Note that curriculum and examinations are identical across colleges in our setting and is a novel feature of our dataset as these features of the educational setting typically vary across treatment and control schools or colleges in the existing literature. The second set of outcomes consists of experimentally elicited behavioral preferences such as competitiveness, overconfidence, and risk.[4] The final set of outcomes deals with the Big Five (Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability) traits, which is a broadly accepted taxonomy of personality traits.

Several interesting findings that vary along the gender line emerge from our analysis. First, enrollment in a selective college leads to gains in scores on standardized university-level examinations for marginally admitted females, and their higher attendance rates are possibly driving this effect. Second, exposure to more able peer environments in these selective colleges makes females less risk averse and less overconfident, pointing towards an increase in rational behavior. Third, we find that marginally admitted males experience a decline in extraversion and conscientiousness as compared to their counterparts in less selective colleges, indicating negative effects of lower ordinal rank in their peer groups. Fourth, enrollment in a selective college generates different effects for students depending on their socioeconomic status. We find that females from economically disadvantaged backgrounds experience greater reductions in risk aversion and are more agreeable compared to students from high income households who enroll in more selective colleges. We also find that the return to enrolling in selective colleges varies by college quality, with males being more susceptible to concerns over low relative rank at the top end of the college quality distribution. Finally, we do not find significant variation in teacher presence across colleges implying differences in peer quality to be driving our main findings. Our results are robust to bandwidth selection, choice of controls, and the level of clustering.

[3]This could also explain the mixed evidence on peer effects in education with some studies finding positive peer effects and others documenting non-linear or no effects (Sacerdote, 2011; Epple and Romano, 2011).

[4]These behavioral traits have been identified to explain a range of labor market outcomes. Competitiveness can explain gender gaps in wages (Niederle and Vesterlund, 2007) and job-entry decisions (Flory et al., 2015). Overconfidence affects entrepreneurial entry (Koellinger et al., 2007; Camerer and Lovallo, 1999) and investment behavior (Malmendier and Tate, 2005). Castillo et al. (2010) and Dasgupta et al. (2015) find that risk preferences have implications for occupational sorting and skill accumulation.

Findings from this paper contribute to a nascent literature examining effects of college selectivity on non-cognitive outcomes.[5] Interestingly, the effects we observe for behavior and personality traits are larger than those for standardized university examination scores. This is in line with findings highlighted in Sacerdote (2011) wherein the peer effects at higher education level are greater on social outcomes related to memberships in sorority/fraternity, smoking, drinking, and criminal behavior than on academic achievement. We also contribute to the literature reporting gender-differentiated responses to educational interventions (e.g., Angrist et al., 2009; Hastings et al., 2006; Jackson, 2010). While females in our setting tend to benefit from higher-quality peer environments, males suffer setbacks in terms of economically valuable personality traits because of the relatively lower rank in their peer groups. Finally, our findings also contribute towards understanding the cognitive and non-cognitive returns to post-secondary education in a developing country context.

The rest of the paper is organized as follows. The college admissions process at the University of Delhi, sampling strategy, and survey details are described in Section 2. The empirical strategy is outlined in Section 3. All results are presented in Section 4. Concluding remarks follow in Section 5.

2 Background and Data

2.1 College Admissions Process

In DU, college admission into three-year undergraduate programs, for most disciplines are based solely on the student's high school exit examination score computed as the average taken over best of four out of five subjects, including language. In the month of June each year, students simultaneously apply to colleges and disciplines within those colleges. Based on applications, 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.[6] All applicants above the cutoff in the discipline are eligible to take admission in the college-discipline. Since there is greater demand for high-quality colleges and they are oversubscribed, the cutoffs for these colleges are significantly and systematically higher than the low-quality colleges, usually across most disciplines. If there are vacancies,

[5]Kaufmann et al. (2015) exploit the Chilean university admission system in a regression discontinuity framework to examine effects of elite institutions on long-run outcomes related to marriage and fertility, and also inter-generational effects on applicants' children.

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

colleges gradually lower their cutoffs through several rounds until all spots are filled.[7] As expected, the better 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 rounds to fill their seats. This process results in an allocation where typically the high-achieving students attend the more selective colleges while the low-achieving students get admitted to the lower quality colleges.[8]

The DU college admission process creates an environment where students who enroll in more selective colleges are exposed to higher-achieving peers as compared to students enrolled in lower quality colleges. This is shown in Table 1. The marginally admitted student is surrounded by peers whose average score on the high school exit examination is 2.5 percentage points higher than peers of a comparable student who just missed the cutoff. In Columns 2 and 3 we show that both male and female students in high-quality colleges are surrounded by high-achieving peers. This systematic difference in peer ability is also evident when we consider performance on another pre-treatment achievement test. Students in India also write a similar high-stakes examination at the end of grade 10. An analysis of our sample's grade 10 scores in Table 1 also points towards the higher peer quality experienced by the marginally admitted student. Figure 1 depicts the corresponding difference in peer quality. Further, we show later in Section 4.3 that other factors such as teacher presence and student-teacher ratios that could explain differences in college quality do not vary significantly around the cutoff, indicating that variation in peer quality explains most of the variation in college quality.

2.2 Sampling Strategy and Subject Recruitment

We constructed our sample in the following manner. First, to ensure representation of colleges along the continuum 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 commerce and/or economics streams. We focus on these two disciplines as they are among the most popular and competitive disciplines and have significantly higher levels of enrollment compared to other disciplines. The 58 colleges that offer courses in these two streams can be

[7] As cutoffs drop between admission rounds, it is possible for students to move 'up' to colleges where they now become eligible. In the sample used for the analysis, we find that 26.5 percent of the students switched colleges during the admission process.

[8] While it is possible for students to seek transfers between colleges after the conclusion of the admission process, it is not very common. In the empirical analysis, we exclude students who reported transferring between colleges at some point after the completion of the admission process.

further categorized into daytime coeducational colleges (31), daytime women-only colleges (10), and evening coeducational colleges (17). Of the 31 daytime coeducational colleges, we further exclude colleges that offer too few courses or use religious criteria or any criteria other than high school exit examination scores for admissions, 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, of which we could implement our study in 15 colleges with varying cutoffs. We collected data on approximately 2000 second and third year students enrolled in these 15 colleges during January-March 2014 in regular class hours, in coordination with the teachers.

2.3 Data

In the first part of the study, we conducted incentivized experiments to obtain measures of behavioral preferences.[9] First, to capture subjects' competitiveness and overconfidence we used a simple number-addition task (similar to Niederle and Vesterlund, 2007). After a practice session, participants had to predict their performance 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 answer if the subject out-performed a randomly selected student of DU who had solved the questions earlier.[10] 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 *overconfidence* as the ratio of the predicted performance to the student's performance in the actual task.

Second, to measure risk preferences, we used the Gneezy and Potters (1997) investment task. 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 was tripled and they also got any amount they set aside. Conversely, if they lost the lottery, they only received the amount that was set aside. We define *risk preference* 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

[9]Subject instructions for the incentivized tasks are available from the authors upon request.

[10]We implemented a pilot version of this game where 40 students from DU had participated, and their performance is used for comparison in the tournament wage scheme.

on family background characteristics, school and college information, academic performance, and participation in extra-curricular activities. To measure cognitive outcomes, we collected data on scores on standardized university examinations. To measure personality traits, we administered the 10-item Big Five inventory (Gosling et al., 2003) that consists of the following traits. *Openness to experience*, a 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 of one's interests and energies oriented towards the outer world of people rather than the inner world of subjective experience, characterized by sociability. *Agreeableness* is related to the tendency to act in a cooperative and unselfish manner. *Emotional stability* (opposite of Neuroticism) is predictability and consistency in emotional reactions with absence of rapid mood changes.

Overall, we conducted 60 sessions with approximately 34 subjects per session. Each session lasted about 75 minutes. No feedback was provided between or after the tasks. All subjects received a show-up fee of Rs. 150. The average additional payment was Rs. 230. All subjects participated only once in the study. To minimize wealth effects, additional payments were based on one of the randomly chosen incentivized tasks.

3 Methodology

3.1 Empirical Specification

For estimating the returns to college quality, we first construct groupings of colleges based on their relative selectivity. We use admission cutoffs, as exogenously announced by the individual colleges, as the criteria to sort the 15 colleges in our sample into four ordered categories such that, (i) colleges in a category have similar cutoffs, and (ii) colleges in the higher categories have admission cutoffs that are consistently higher than the cutoffs of colleges that belong to the lower categories. The 15 colleges in our sample are consequently given four ranks ranging from 1 (highest rank) to 4 (lowest rank).

Next, for each rank we compute the minimum score required for admission into the group. Cutoffs vary by student type where students differ in their current discipline (commerce and economics), academic concentration in high school (science, commerce, and humanities), gender, and year of entry. For example, a student seeking admission into economics, having studied science in high school faces a different cutoff from a student who studied commerce during high school. Further, some colleges also offer discounted cutoffs to female applicants. Thus, for each rank of colleges we get a set of cutoffs that define the minimum score required by each student type for admission into that college rank.

We are interested in estimating the returns to enrollment in a more selective college group for which we construct three samples. In the first sample, colleges in rank 1 are assigned as the treated group (high-quality college) and the remaining colleges (in ranks 2, 3 and 4) are assigned as lower-quality colleges. Thus, in the first sample a student is considered to be in the treated group if she is enrolled in any of the colleges in rank 1. In the next sample, colleges in ranks 1 and 2 are assigned to the treated group and the remaining colleges (ranks 3 and 4) are assigned to the low-quality college group. Finally, a third sample is constructed where colleges ranked 1, 2, and 3 are assigned to the high-quality college group and colleges in rank 4 are in the low-quality college group. Following Abdulkadiroğlu et al. (2014) and Pop-Eleches and Urquiola (2013), we construct our final analysis sample by 'stacking' the three samples together, and estimate a single average treatment effect measuring the impact of enrollment in a high-quality college.

Of course, enrollment in the high-quality college is endogenous as not all students who are eligible to enroll in a higher quality college do so.[11] To account for this, we use a "fuzzy" regression discontinuity (RD) design where enrollment is instrumented by eligibility to enroll in a more selective college (Hahn et al., 2001; Lee and Lemieux, 2010). In particular, we estimate the following set of instrumental variable regressions where the first-stage regression is:

$$TR_{ij} = \alpha_0 + \alpha_1 T_{ij} + \alpha_2 d_{ij} + \alpha_3 d_{ij}^2 + \alpha_4 d_{ij} T_{ij} + \alpha_5 d_{ij}^2 T_{ij} + \sum_{l=6}^{K} \alpha_l X_{lij} + \eta_j + \epsilon_{ij} \tag{1}$$

and the corresponding second-stage regression is:

$$Y_{ij} = \delta_0 + \delta_1 TR_{ij} + \delta_2 d_{ij} + \delta_3 d_{ij}^2 + \delta_4 d_{ij} TR_{ij} + \delta_5 d_{ij}^2 TR_{ij} + \sum_{l=6}^{K} \delta_l X_{lij} + \eta_j + \mu_{ij} \tag{2}$$

[11] Similarly, we also have a few instances where students who are ineligible for a higher ranked college are admitted to that college. Overall, in the stacked sample used in the analysis, only 0.35 percent of the subjects who have a negative distance from the cutoff are enrolled in a higher ranked college and approximately 6 percent of the subjects who have a positive distance from the cutoff are enrolled in a lower ranked college.

where Y_{ij} in equation (2) is the outcome variable of interest for student i of type j. Equation (1) is a linear probability model where TR_{ij} takes the value 1 if student i of type j is treated, i.e., enrolled in a high-quality college. The running variable, d_{ij}, is computed as the difference between student $i's$ high school exit examination score and the relevant college rank-specific cutoff faced by her type j. The instrument is a dummy variable for eligibility, T_{ij}, that takes a value 1 if d_{ij} is non-negative, 0 otherwise. We allow for non-linearity in the relationship between the outcomes and the running variable by including a quadratic specification in the running variable as well as allow the estimated returns to college quality to vary on each side of the cutoff by allowing interactions between the TR dummy and d_i and d_i^2. Our regressions also include cutoff fixed effects (η_j) where the cutoffs vary by student types. This allows us to obtain the relevant counterfactual for a student enrolled in the high-quality college - a student of the same type (i.e., currently enrolled in the same discipline, with the same high school academic concentration, same gender, and same year of admission) who marginally missed the relevant cutoff. We also include a vector of predetermined characteristics (Xs) such as mother's education, father's education, private school enrollment, age, family income, and religion in the regressions to improve the precision of our estimates. Finally, μ_{ij} and ϵ_{ij} are iid error terms.

The coefficient estimate on TR in equation (2) gives us the local average treatment effect (LATE) of being enrolled in a selective college group. Since the running variable is discrete, following Lee and Card (2008), we cluster our standard errors with respect to 0.25 bins of the running variable. The choice of the bandwidth is another important issue in RD analysis. Since we have various outcome variables, we fix the bandwidth to be 5 percentage points around the cutoff for the main analysis. Nonetheless, in Section 4.4, we show that our results are robust to using outcome-specific optimal bandwidths determined by the procedure outlined in Calonico et al. (2014).

For the analysis, we exclude all those students whose admissions were not based on their high school exam scores. This includes students belonging to historically disadvantaged backgrounds (Scheduled Castes, Scheduled Tribes, and Other Backward Classes) 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. From an initial sample of 2065, 1331 subjects remain after making exclusions as discussed above.[12] After stacking our data and limiting to a

[12]In our initial sample, 29 percent are affirmative action beneficiaries, 4.8 percent got admitted based

bandwidth of five percentage points around the cutoff, the analysis sample is 2395. Finally, as the literature on educational interventions, and more specifically on the effects of school and college quality documents significant heterogeneity by gender (e.g., Kling et al., 2005; Hastings et al., 2006; Jackson, 2010), we also report our results for samples of males and females separately.

As we wish to estimate the effects of admission into a higher quality college versus the counterfactual of a lower quality college, the ideal sample would comprise students who strictly prefer higher quality colleges to the lower quality ones such that a score above the cutoff would lead to admission in a higher quality college, and scoring below the relevant cutoff would result in admission in a lower quality college. The student allocation mechanism used in DU is different from the more commonly observed centralized mechanisms such as the Boston school choice mechanism (Abdulkadiroğlu et al., 2014), the student or college proposing deferred acceptance mechanisms, or the top trading cycle mechanism. In DU, students are admitted through a decentralized admission process wherein they apply to college-disciplines individually and do not have to submit a preference ranking over disciplines and/or colleges to any central authority. Therefore, this decentralized allocation process does not provide the underlying preferences of the applicants and all we observe is the current college that the student is enrolled in, along with her high school exit examination score, and the cutoffs she faced at the time of admission. Nonetheless, note that with a fixed supply of seats, the higher cutoffs at colleges are a reflection of (greater) excess demand for those seats. It is then reasonable to assume that the average student prefers admission into a college with higher cutoffs as opposed to one with lower cutoffs.

3.2 Testing Validity of the RD Design

The 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 on. However, this is not possible under the admission process in DU. First, high school exit examinations follow a double blind grading procedure,

on sports and other activities, 0.3 percent migrated within or across colleges, and 0.6 percent provided insufficient information.

making manipulation difficult, if not outright impossible. Second, at the time of application to DU colleges, students are not aware of the precise cutoffs that will determine admissions that year.[13] Moreover, since the rule for determining these cutoffs is never public knowledge, students cannot perfectly predict future cutoffs. Overall, it is virtually impossible for students to perfectly manipulate the side of the college cutoff they will ultimately fall on.[14]

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, formally check for discontinuities in other predetermined characteristics such as mother's education, father's education, private high school enrollment, age, family income, and religion by estimating the following reduced form regression:

$$X_{ij} = \beta_0 + \beta_1 T_{ij} + \beta_2 d_{ij} + \beta_3 d_{ij}^2 + \beta_4 d_{ij} T_{ij} + \beta_5 d_{ij}^2 T_{ij} + \eta_j + \upsilon_{ij} \tag{3}$$

Where X is the vector of predetermined background characteristics and the right hand side variables are as defined in equations (1) and (2) above. The results from these regressions are presented in Table 2. We find that the impact of the treatment indicator, that is, being eligible to enroll in a higher quality college on the predetermined variables is mostly small and never significantly different from zero, confirming the validity of the RD design for the pooled sample (Panel A), males (Panel B), and females (Panel C). The corresponding graphical representations are provided in Figures A1 - A3 in the online Appendix.

Next, we check if the probability of enrollment is indeed discontinuous at the cutoff. In Figure 2, we plot the proportion of students enrolled in a high-quality college in each 0.25 bin against the distance from the cutoff. This is done for the pooled sample and separately for males and females as well. In all three sub-figures, we see a clear discontinuity in the probability of enrolling in a more selective college at the cutoff, indicating the appropriateness of the RD design. A formal estimation of the first-stage relationship between enrollment in a selective

[13] Based on historical trends, students may have an estimate of the range of the cutoff, but this does not invalidate our analysis since perfect manipulation is impossible.

[14] The RD literature uses the presence of bunching just above the threshold as an indicator of manipulation (typically tested using the McCrary test). However, the college admission process followed in DU by construction results in bunching of students just above the threshold and hence is not useful for detecting manipulation in the sample.

college and eligibility is provided in Table 3. We find that on average, students who are eligible to enroll in a selective college are 68 percent more likely to do so, indicating a strong revealed preference for more selective colleges. We find similar strong effects of the eligibility to enroll in a selective college for both males and females. As compliance with DU admission rules is not perfect, we use a fuzzy RD design and in the sections that follow, present results from the corresponding IV specification discussed in equations (1) and (2).

4 Results

4.1 Summary Statistics

In Table 4, we present descriptive statistics for our sample. In Panel A, we summarize average performance on standardized university-level examinations, our measure of academic attainment during college.[15] The average score is 70 percent with no significant gender differences.

In Panel B, we summarize average choices of the elicited behavioral preferences: competitiveness, overconfidence, and risk. In our sample, 31 percent of the subjects are deemed as being competitive as they choose the tournament payment scheme. The average student is overconfident as the ratio of the expected number of correct answers to the number correctly solved in the actual task is 1.6, significantly higher than 1. 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 that subjects often irrationally overestimate their own abilities across tasks (e.g., Niederle and Vesterlund, 2007; 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 as reported in Charness and Viceisza (2016). It is not surprising that there are significant gender differences with males being more competitive and less risk averse than females (see Niederle, 2016 for a review).

In Panel C, we summarize subjects' Big Five personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability. In our sample, subjects report a higher score on agreeableness, conscientiousness, and openness to experience than they do for extraversion and emotional stability. There are significant differences by gender

[15] The university follows a semester system where an academic year consists of 2 semesters, with exams held in December and May. Since our study was conducted during January-March, for second and third year students, we have the average exam scores based on 3 semesters and 5 semesters respectively.

with females being more extrovert, conscientious and agreeable, and less emotionally stable than males ($p - value \leq 0.01$ in all cases except extraversion). Similar gender differences in personality traits are also noted across several cultural contexts (Schmitt et al., 2008).

Finally, in Panel D, we present descriptive statistics on background characteristics. The average age of the students is close to 20, with little variation. Over 90 percent of the students are Hindus (the dominant religion in India), 85 percent attended a private high school, and 73-79 percent of students have either a highly educated mother or father (college degree or higher). A third of the sample comes from low-income households (i.e. those earning less than Rs. 50,000 per month).[16]

4.2 Returns to College Quality: Cognitive, Behavioral, and Personality

In Table 5, we present the impacts of enrollment in a more selective college on cognitive (in Panel A), behavioral (in Panel B), and personality outcomes (in Panel C) for the pooled sample, males, and females in Columns 1, 2, and 3 respectively. These are IV estimates obtained from equation (2). While curriculum and examinations are the same within a discipline across colleges of DU, marginal admission into a more selective college exposes students to high-achieving peers. Looking at the impact estimates on the standardized university-level examination scores for the pooled sample in Column 1 of Panel A, we find that compared to students in lower quality colleges, marginally admitted students in higher quality colleges experience a 1.1 percentage point increase in their average university examination scores. Upon further examining these effects by gender, it is apparent that this overall impact is entirely driven by the significant effects on females' test scores with no effect for males (Columns 2 and 3). In particular, females, on average, score 2.6 percentage points higher on the university examinations relative to females in lower quality colleges, translating into an approximate increase of 3.8 percent over the control group's mean of 69 percent. Our finding that females make significant academic gains from exposure to peer environments with little or no accompanying effects on males has also been found in other studies of school and college quality (e.g., Jackson, 2010; Hastings et al., 2006) as well as other educational interventions (e.g., Angrist et al., 2009; Angrist and Lavy, 2009). Further, we show later in Section 4.3 that females enrolled in more selective colleges are almost 31 percentage points

[16]According to the nationally representative India Human Development Survey of 2011-12, the average yearly income for upper caste households is approximately Rs. 180,000, indicating that our analysis sample fares significantly better than the average.

more likely to have higher attendance rates than their counterparts in less selective colleges. On the other hand, we find no such effect of college quality on male attendance rates. This gender difference in attendance rate is likely to explain the observed gender gap in academic returns to better college and peer environments.

We also estimate the returns to enrollment in a selective college on three measures of behavior: competitiveness, overconfidence, and risk. The results are reported in Panel B of Table 5. Pooled results indicate that the marginally admitted student experiences a decline in overconfidence with no significant effects on competitiveness and risk preferences. On disaggregating the sample by gender, we find no significant effects on males. We observe overconfidence among marginally admitted females to reduce by 0.70 units or, approximately 42 percent of the control mean. We also find that females enrolled in more selective colleges invest almost 13 percentage points more in the investment game, thereby being less risk averse than their female counterparts who just miss out on a more selective college. This effect is substantial given that the control mean is 43.3 percent. To the extent that females are more risk averse than males, and this gender gap in risk preferences has implications for occupational choice and other economic decision-making, this result suggests that higher quality colleges may result in a narrowing of this gender gap. The observed decline in risk aversion and overconfidence points towards an increase in rationality among marginally admitted females. Specifically, as per the expected utility theory framework, given the nature of the investment game used to elicit risk preferences as described in Section 2.3, a risk-neutral individual should invest the full amount in the risky lottery. Therefore, an increase in the proportion invested in the risky lottery by females in selective colleges suggests that exposure to, and learning from, higher ability peer groups leads them to assess the risk in a more rational manner. Similarly, for the marginal student, being surrounded by smart peers, allows her to update her beliefs about her (relative) ability, leading to a decline in overconfidence. Since overconfidence is positively and risk aversion is negatively related to competitiveness, a decline in risk aversion and overconfidence could plausibly explain why we do not observe any significant effects of college quality on competitiveness.

The last set of impact estimates pertains to personality: Big Five traits of openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability (see Panel C, Table 5). In the pooled sample, we find that enrollment in a more selective college negatively affects extraversion by 0.27 standard deviations with no effect on other traits. We find substantial gender differences in the impact on personality: extraversion and conscientiousness among marginally admitted males reduces by 0.48 standard deviations and 0.55

standard deviations, respectively. Taken together, these estimates for male students suggest a diminished self-concept stemming from their lower academic position within their college rank, resulting in negative effects on economically valuable personality traits. Murphy and Weinhardt (2016) also find males to be influenced more significantly on account of rank concerns. Using alternative measures as proxies for these personality traits reinforces our findings. In results reported in Table A1 in the online Appendix, membership in college-level societies, another measure of extrovert behavior, is also lower among males enrolled in higher quality colleges. Similarly, we also find that males at the margin of admission in higher quality colleges report lower grit, which is highly correlated with conscientiousness.[17] We also observe a decline in openness to experience and agreeableness for males, though neither is statistically significant. In light of recent findings that show that conscientiousness and extraversion matter for academic performance (Lundberg, 2013), the adverse effects on these personality traits for marginally admitted males might explain why we observe no gains in test scores from exposure to a better college environment.

4.3 Pathways

Owing to the design of the admissions process in colleges at DU, we have so far shown and argued that differences in peer quality is the likely channel driving our main results, as it varies significantly across colleges. In this section, we explore a variety of other potential channels that could explain our main findings.

In Column 1 in Table 6, we examine differences in attendance rates. We construct a binary variable for high attendance that takes a value 1 if subjects report having class attendance rates of 75 percent and higher, and 0 if attendance is below 75 percent. We find that while there is no significant difference for males in the probability of high attendance, females enrolled in selective colleges have a greater probability of high attendance than females in less selective colleges. This indicates that they are present in class more often and therefore have an opportunity to learn from and engage with their peers, making it one of the competing explanations for gains on cognitive and behavioral outcomes. This finding fits in with the general observed pattern of females having better study habits (Angrist et al., 2009; Angrist and Lavy, 2009; Hastings et al., 2006).

Next, we examine relative attendance by asking subjects to indicate attendance relative

[17] Grit is the tendency to sustain interest in and effort towards very long-term goals (Duckworth and Quinn, 2009).

to their classmates. In Column 2, we construct an outcome variable that takes the value 1 if the subject attended classes less often than her classmates. We find that marginally admitted males are more likely to skip classes than their classmates. This points towards weakened self-concept among males on account of their lower academic position in their college rank, potentially indicating higher mental or psychic costs of investing effort. Elsner and Isphording (2016a) also find a similar effect in that students with lower ordinal rank are more likely to be absent from classes.

Subjects could also experience learning gains due to complementary investments in education undertaken by parents and students in the form of external tutorials and remedial classes.[18] These can improve test scores independent of the college and peer environment. However, as shown in Column 3 of Table 6, we do not find a discontinuity in the probability of using external tutorials for either males or females.

Finally, differences in indicators of teacher quality and presence could also matter for students' academic and non-academic outcomes (e.g., Hoffmann and Oreopoulos, 2009; Chetty et al., 2014; Jackson, 2012). It should be noted that teacher salaries are the same across colleges in DU. As a measure of teacher quality and presence, we asked students if classes were cancelled frequently by teachers. Results in Column 4 show no discontinuity in the probability of classes being cancelled. Finally, results in Column 5 indicate that student-teacher ratio, an additional measure of college quality, also does not vary around the cutoff.

4.4 Robustness

We show here that the LATE estimates reported earlier in Table 5 are robust to several econometric concerns such as: inclusion of controls, choice of the polynomial order, bandwidth selection, and estimation technique. These results are presented for the pooled sample, males, and females in Panels A, B and C respectively of Tables 7 and 8 .

First, while our main estimates control for several predetermined background characteristics to improve precision, we now show that the results remain robust to excluding these controls. Second, to check for specification bias arising from the choice of second-order polynomial function, we present the impact of enrolling in a selective college on all outcomes using a flexible cubic polynomial function and find that the results are mostly similar to the ones presented earlier in Table 5. Third, while we have used rectangular weights in the main

[18] Another parental response could be spending time with children to help them with academic materials and homework as in Pop-Eleches and Urquiola (2013). However, that is unlikely at college level.

analysis, we find that using triangular weights that assign greater weights to observations closer to the cutoff does not qualitatively alter the results. Fourth, while we have used a common bandwidth of 5 percentage points for all the outcomes in Table 5, we now restrict our data to the optimal bandwidth prescribed by Calonico et al. (2014) separately for each outcome variable, and find our results to be robust to the width of the window around the cutoff. Finally, our results remain robust to clustering at the level of the student or the session.[19]

As discussed in Section 3.1, in estimating the effect of admission into a higher quality college versus a lower quality college, we implicitly assume that students prefer a higher quality college to a lower quality one. We now show that our results are largely robust to relaxing this assumption. In the survey, we asked students to rank a subset of the surveyed colleges across our four ranks. While we did ask students to rank the colleges as they would have at the time of admission, this ranking is bound to be subject to measurement error. Nonetheless, we use this information in the following way to assess the robustness of our results. While constructing each of our RD samples, as discussed in Section 3.1, we limit our sample to students who strictly rank all the treated colleges higher than the lower-quality colleges and do not rank any of the low-quality colleges at least as high as any of the treated colleges. While the sample now is limited, we find that the effects on most behavioral and personality traits continue to hold (Table A2 in the online Appendix).

4.5 Heterogeneity

In this section, we explore if the effects of college quality vary by, (i) family background characteristics, and (ii) the degree of college selectivity.

Current research indicates that growing up in households characterized by low socioeconomic status can adversely affect the formation and development of behavior and personality traits because of lower parental investment in terms of time and money (e.g., Deckers et al., 2016; Fletcher and Wolfe, 2016). If this is indeed the case, then can higher quality college environments have compensatory effects on the development of these socioemotional skills? On the other hand, there may be dynamic complementarities as proposed by Cunha and Heckman (2007) such that students from well-off backgrounds may be equipped with a better stock of skills owing to early investments that allow them to gain more from their college environments. We examine the interactive effects of family background characteristics with

[19]These results are available from the authors upon request.

college quality to allow for the returns to enrolling in a selective college to vary by family income and parental education. The results are reported in Table 9. Given the gender-differentiated returns to college quality noted so far, we report the heterogeneity results for males and females separately. The coefficients of interest are the interaction terms of the indicator of enrollment in a more selective college with the indicator of low income/low parental education.[20]

Panels A and B of Table 9 report the heterogeneous effects of low income and low parental education for males respectively while Panels C and D report the results for females. The first column indicates that there is no heterogeneity in the cognitive returns to college quality by family background. Columns 2-4 report the results for behavioral preferences: competitiveness, overconfidence, and risk. Column 4 shows that females from low-income households enrolled in more selective colleges invest 5.6 percentage points more compared to females from high-income households that are enrolled in a selective college. Similarly, among those enrolled in more selective colleges, females with less educated parents invest significantly more than those whose parents are highly educated. As high socioeconomic status is usually correlated with less risk averse behavior (e.g., Dohmen et al., 2011), more selective colleges mitigate the gap in risk preferences between students from varying socioeconomic backgrounds. Finally, on examining the socioemotional traits in Columns 5-9, we find that females from low-income households enrolled in more selective colleges report higher scores on agreeableness than those from high-income households, implying some gains in their ability to engage in interpersonal interactions. However, we do not find a corresponding effect when examining heterogeneity by parental education. Finally, the remaining columns indicate that we do not find any differential effects on other Big Five traits of being in selective colleges based on socioeconomic status.

We proceed to explore if the effects vary by the selectivity of the college. The existing literature has mainly studied effects of enrollment in top educational institutions (e.g., Hoekstra, 2009; Abdulkadiroğlu et al., 2014) or average effects of enrolling in relatively more selective institutions using data from a range of institutions (e.g., Jackson, 2010; Lucas and Mbiti, 2014). However, returns to school and educational quality may be non-linear and vary across the quality distribution. For example, Hoekstra et al. (2016) examine schools of varying selectivity within the same educational context in China and find effects stemming

[20] In terms of the IV regressions discussed in Section 3, we add the interaction of the indicator of enrollment in a selective college and the indicator of socioeconomic status as an additional endogenous regressor and add the interaction of the indicator of eligibility for enrollment in a selective college and the indicator of socioeconomic status as an additional instrument.

from enrollment in only the most elite schools. In a similar vein, in our setting, we examine if behavioral responses to college and peer environments differ depending on how selective the college is. For this purpose, we re-estimate our regressions separately examining (i) the effect of enrolling in a rank 1 (most selective) colleges in Panels A and B of Table 10, and (ii) the effects of college quality *excluding* rank 1 college cutoffs in Panels C and D of Table 10. The returns to college quality may vary across these two samples as the scope for improvement based on learning from peers may be lower in rank 1 colleges. Furthermore, the adverse effects of lower relative rank on academic self-concept may be more acutely felt in the more selective colleges. We find that enrolling in a rank 1 college reduces conscientiousness, openness to experience, and overconfidence among marginally admitted males, and an increase in risk taking and reduction in overconfidence for females. In contrast, we find that excluding rank 1 college cutoffs reduces extraversion for males and increases risk taking among females. Overall, the results suggest that males are more likely to be susceptible to relative rank concerns in the most selective colleges which results in negative effects on personality and behavior reported in Panel A compared to Panel C, Table 10. On the other hand, for females, the results in Panel B and Panel D remain largely similar.

5 Conclusion

The existing empirical work on the returns to college quality has largely focused on test scores as outcomes of human capital with resulting mixed evidence. Scant attention has been paid to non-cognitive and socioemotional traits, facets of human capital that recent research has documented as being tremendously important for one's economic progress.

In this paper, our aim has been to fill this critical gap by examining the effects of college selectivity on cognitive, behavioral, and socioemotional outcomes, using novel data collected from a large sample of students at a leading Indian university. Exploiting the variation in college admission cutoffs, we compare students just above the cutoff with those just below the cutoff to determine the causal impact of enrollment in a selective college, where they are exposed to relatively high-achieving peers. We find that a marginally admitted student in a more selective college experiences an improvement in scores on standardized university exams, and this effect is driven by females. In terms of behavioral and personality traits, we find that females just above the cutoff become less risk averse and less overconfident, indicating an increase in rationality. On the other hand, males in these colleges experience declines in extraversion and conscientiousness pointing towards a weakened self-concept due to a lower relative rank in their peer group. Further, we are also able to show that variation in college quality stems mainly from variation in peer quality with no differences in teacher presence or student-teacher ratios around the cutoff.

Some caveats remain. First, it should be noted that our study does not encompass the entire population of University of Delhi students. Also, since this is one of the premier universities in India, its students are not representative of the average Indian college student. Second, while at this point the study is unable to comment on observable labor market outcomes of this cohort of students, in future work, we aim to do so.

References

Abdulkadiroğlu, A., Angrist, J.D., and Pathak, P.A. (2014). The Elite Illusion: Achievement Effects at Boston and New York Exam Schools. *Econometrica*, 82(1), 137-196.

Ajayi, K.F. (2014). Does School Quality Improve Student Performance? New Evidence from Ghana. Working Paper.

Almas, I., Cappelen, A.W., Salvanes, K.G., Sorensen, E.O., and Tungodden, B. (2016). What explains the gender gap in college track dropout? Experimental and administrative evidence. *American Economic Review: Papers & Proceedings*, 106(5), 296-302.

Almlund, M., Duckworth, A.L., Heckman, J.J. and Kautz, T. (2011). Personality psychology and economics, in E.A. Hanushek, S. Machin and L. Woessmann, (eds.), *Handbook of the Economics of Education*, vol. 4, pp. 1-181, Amsterdam: North-Holland.

Angrist, J., Lang, D., and Oreopoulos, P. (2009). Incentives and Services for College Achievement: Evidence from a Randomized Trial. *American Economic Journal: Applied Economics*, 1(1), 136-63.

Angrist, J., and Lavy, V. (2009). The Effects of High Stakes High School Achievement Awards: Evidence from a Randomized Trial. *American Economic Review*, 99(4), 301-331.

Borghans, L., Duckworth, A.L., Heckman, J.J., and ter Weel, B. (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources*, 43(4), 972-1059.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, 82(6), 2295-2326.

Camerer, C. F. and D. Lovallo (1999). Overconfidence and Excess Entry: An Experimental Approach. *American Economic Review*, 89, 306-318.

Castillo, M., Petrie, R. and Torero, M. (2010). On the Preferences of Principals and Agents. *Economic Inquiry*, 48(2), 266-273.

Charness, G., and Viceisza, A. (2016). Three risk elicitation methods in the field: evidence from rural Senegal. *Review of Behavioral Economics*, 3(2), 145-171.

Chetty, R., Friedman, J.N., Rockoff, J.E. (2014). Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood. *American Economic Review*, 104(9), 2633-79.

Chuang, Y., and Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics*, 117, 151-170.

Cicala, S., Fryer, R. G., and Spenkuch, J. L. (2016). Comparative Advantage in Social Interactions. Working paper.

Cunha, F., and Heckman, J.J. (2007). The technology of skill formation. *American Economic Review Papers & Proceedings*, 97(2), 31-47.

Dasgupta, U., Gangadharan, L., Maitra, P., Mani, S., and Subramanian, S. (2015). Choosing to be Trained: Do Behavioral Traits Matter? *Journal of Economic Behavior & Organization*, 110, 145-159.

Deckers, T., Falk, A., Kosse, F., and Schildberg-Hörisch, H. (2015). How Does Socio-Economic Status Shape a Childs Personality? IZA Working Paper No. 8977.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522-550.

Duckworth, A.L, and Quinn, P.D. (2009). Development and validation of the Short Grit Scale (Grit-S). *Journal of Personality Assessment*, 91, 166-174.

Elsner, B., and Isphording, I. (2016a). A Big fish in a small pond: Ability rank and human capital investment. *Journal of Labor Economics*, forthcoming.

Elsner, B., and Isphording, I. (2016b). Rank, sex, drugs, and crime. *Journal of Human Resources*, forthcoming.

Epple, D., and Romano, R. (2011). Peer effects in education: A survey of the theory and evidence. In J. Benhabib, A. Basin and M. Jackson (Eds.) *Handbook of Social Economics*, 1053-1163.

Feld, J., and Zölitz, U. (2017). Understanding peer effects: on the nature, estimation, and channels of peer effects. *Journal of Labor Economics*, forthcoming.

Fletcher, J. M., and Wolfe, B. (2016). The importance of family income in the formation and evolution of non-cognitive skills in childhood. *Economics of Education Review*, 54, 143-154.

Flory, J. A., Leibbrandt, A., and List, J. A. (2015). Do competitive work places deter female workers? A large-scale natural field experiment on job entry decisions. *Review of Economic Studies*, 82(1), 122-155.

Gneezy, U. and Potters, J. (1997). An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2), 631-645.

Gosling, S.D., Rentfrow, P.J., and Swann Jr., W.B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37, 504-528.

Hahn, J., Todd, P., and Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1), 201-209.

Hanushek, E.A., and Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3), 607-668.

Hastings, J.S., Kane, T., and Staiger, D. (2006). Gender, performance and preferences: do girls and boys respond differently to school environment? Evidence from school assignment by randomized lottery. *American Economic Review Papers & Proceedings*, 96(2), 232-236.

Heckman, J.J., Stixrud, J., and Urzúa, S. (2006). The effects of cognitive and non-cognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3), 411-482.

Hoekstra, M. (2009). The effect of attending the flagship state university on earnings: a discontinuity-based approach. *Review of Economics and Statistics*, 91(4), 717-724.

Hoekstra, M., Mouganie, P., and Wang, Y. (2016). Peer quality and the academic benefits to attending better schools. Working Paper.

Hoffmann, F., and Oreopoulos, P. (2009). Professor qualities and student achievement. *Review of Economics and Statistics*, 91(1), 83-92.

Jain, T., and Kapoor, M. (2015). The impact of study groups and roommates on academic performance. *Review of Economics and Statistics*, 97(1), 44-54.

Jackson, C. K. (2010). Do Students Benefit from Attending Better Schools? Evidence from Rule-based Student Assignments in Trinidad and Tobago. *Economic Journal*, 120(549), 1399-1429.

Jackson, C. K. (2012). Non-Cognitive Ability, Test Scores, and Teacher Quality: Evidence from 9th Grade Teachers in North Carolina. NBER Working Paper No. 18624.

Kaufmann, K.M., Messner, M., and Solis, A. (2015). Elite higher education, the marriage market, and intergenerational human capital. Working Paper.

Kling, J.R., Ludwig, J., and Katz, L.F. (2005). Neighborhood effects on crime for female and male youth: evidence from a randomized housing mobility experiment. *Quarterly Journal of Economics*, 120(1), 87-130.

Koellinger, P., Minniti, M., and Schade, C. (2007). 'I think I can, I think I can': Overconfidence and Entrepreneurial Behavior. *Journal of Economic Psychology*, 28, 502 - 527.

Lee, D.S., and Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, 142, 655-674.

Lee, D. S., and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48(2), 281-355.

Lucas, A.M., and Mbiti, I.M. (2014). Effects of School Quality on Student Achievement: Discontinuity Evidence from Kenya. *American Economic Journal: Applied Economics*, 6(3), 234-263.

Lundberg, S. (2013). The College Type: Personality and Educational Inequality. *Journal of Labor Economics*, 31(3), 421-441.

Malmendier, U., and Tate, G. (2005). CEO overconfidence and corporate investment. *Journal of Finance*, 60(6), 2661-2700.

Marsh, H., Seaton, M., Trautwein, U., Ludtke, O., Hau, O'Mara, A., and Craven, R. (2008). The Big Fish Little Pond Effect Stands Up to Critical Scrutiny: Implications for Theory, Methodology, and Future Research. *Educational Psychology Review*, 20(3), 319-350.

Murphy, R., and Weinhardt, F. (2016). Top of the class: The importance of ordinal rank. Working Paper.

Niederle, M. (2016). Gender. In J.H. Kagel and A.E. Roth (Eds.) *Handbook of Experimental Economics*, Vol. 2, 481-553.

Niederle, M. and Vesterlund, L. (2007). Do Women Shy Away from Competition? Do Men Compete to Much? *Quarterly Journal of Economics*, 122(3), 1067-1101.

Oreopoulos, P., and Salvanes, K.G. (2011). Priceless: The nonpecuniary benefits of schooling. *Journal of Economic Perspectives*, 25(1), 159-184.

Pop-Eleches, C., and Urquiola, M. (2013). Going to a Better School: Effects and Behavioral Responses. *American Economic Review*, 103(4), 1289-1324.

Rubinstein, Y., and Sekhri, S. (2013). Public Private College Educational Gap in Developing Countries: Evidence on Value Added versus Sorting from General Education Sector in India. Working paper.

Saavedra, J. (2009). The learning and early labor market effects of college quality: a regression discontinuity analysis. Working paper.

Sacerdote, B. (2011). Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far? *Handbook of the Economics of Education*, Vol. 3, 249-277.

Schmitt, D. P., Realo, A., Voracek, M., and Allik, J. (2008). Why can't a man be more like a woman? Sex differences in Big Five personality traits across 55 cultures. *Journal of Personality and Social Psychology*, 94, 168-182.

Schurer, S., Kassenboehmer, S.C., and Leung, F. (2015). Do universities shape their students personality? IZA DP No. 8873.

Specht, J., Egloff, B., and Schmukle, S.C. (2011). Stability and change of personality across the life course: the impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology*, 101(4), 862-882.

Figures and Tables

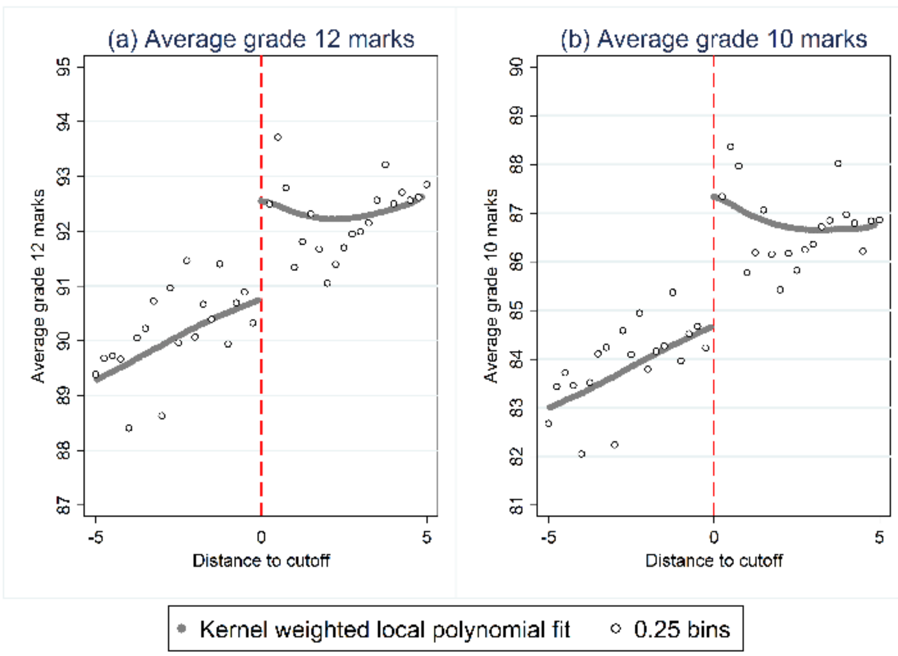

Figure 1: College quality and peers

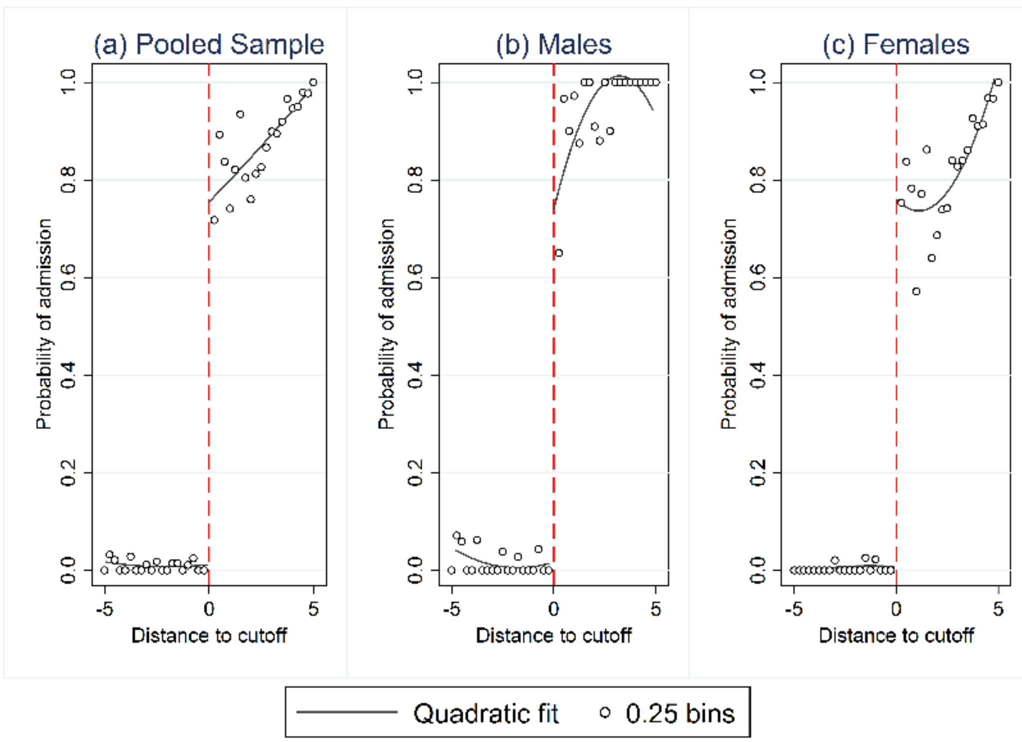

Figure 2: First Stage Relationship

Table 1: Average Peer Quality

	Full Sample (1)	Males (2)	Females (3)
Av. grade 12 score	2.523***	2.512***	2.743***
	(0.254)	(0.350)	(0.409)
Observations	2359	1039	1320
Av. grade 10 score	3.137***	2.805***	3.559***
	(0.320)	(0.462)	(0.535)
Observations	2352	1037	1315

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, family income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 2: Controls Balance

	Age (1)	Mother's edu. (2)	Father's edu. (3)	Religion (4)	Private School (5)	Low Income (6)
Panel A: Full Sample						
1(Above Cutoff)	0.044	0.021	-0.035	-0.042	0.023	0.027
	(0.108)	(0.051)	(0.083)	(0.047)	(0.055)	(0.093)
Observations	2368	2393	2393	2393	2393	2393
Panel B: Males						
1(Above Cutoff)	0.043	-0.040	-0.062	-0.028	0.006	0.088
	(0.188)	(0.076)	(0.096)	(0.068)	(0.070)	(0.105)
Observations	1043	1059	1059	1059	1059	1059
Panel C: Females						
1(Above Cutoff)	0.059	0.066	-0.031	-0.058	0.033	-0.034
	(0.099)	(0.065)	(0.076)	(0.043)	(0.052)	(0.106)
Observations	1325	1334	1334	1334	1334	1334

Notes: This table reports the reduced form estimates using the flexible second order polynomial described in the text. Above cutoff is an indicator function that takes a value 1 if the student's high school examination score is greater than or equal to her type specific cutoff and 0 otherwise. Religion is an indicator variable for being a Hindu; low income is an indicator variable for monthly family income being below Rs. 50,000; mother's and father's education are indicator variables for tertiary education; private school is an indicator variable for graduation from a private high school. All regressions include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 3: First Stage Discontinuity

	Full Sample (1)	Males (2)	Females (3)
Without controls	0.682***	0.699***	0.635***
	(0.062)	(0.103)	(0.054)
With controls	0.683***	0.704***	0.636***
	(0.061)	(0.100)	(0.053)
Observations	2368	1043	1325

Notes: This table shows the first stage discontinuity results using a flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 4: Summary Statistics

	Full Sample (1)	Males (2)	Females (3)	Difference (4)
Panel A: Cognitive outcomes				
University exam score	70.44	70.19	70.64	-0.45
	(7.39)	(7.43)	(7.36)	
Panel B: Behavioral preferences				
Competitiveness	0.31	0.41	0.24	0.17***
	(0.46)	(0.49)	(0.43)	
Overconfidence	1.64	1.66	1.63	0.03
	(1.22)	(1.20)	(1.24)	
Risk preference	46.59	49.88	43.99	5.89***
	(19.08)	(21.71)	(16.24)	
Panel C: Personality traits				
Extraversion score	4.77	4.69	4.83	-0.14*
	(1.43)	(1.43)	(1.42)	
Agreeableness score	5.20	4.97	5.38	-0.41***
	(1.16)	(1.16)	(1.12)	
Conscientiousness score	5.31	5.20	5.40	-0.20***
	(1.26)	(1.29)	(1.23)	
Emotional stability score	4.54	4.65	4.45	0.20***
	(1.38)	(1.40)	(1.36)	
Openness to experience score	5.42	5.44	5.41	0.03
	(1.12)	(1.10)	(1.14)	
Panel D: Socioeconomic characteristics				
Age	19.66	19.69	19.65	0.04
	(0.86)	(0.86)	(0.86)	
Religion	0.92	0.92	0.93	-0.01
	(0.27)	(0.28)	(0.26)	
Private School	0.85	0.85	0.84	0.01
	(0.36)	(0.36)	(0.36)	
Low Income	0.30	0.30	0.31	-0.01
	(0.46)	(0.46)	(0.46)	
Mother's Education	0.75	0.73	0.77	-0.04*
	(0.43)	(0.44)	(0.42)	
Father's Education	0.78	0.78	0.79	-0.00
	(0.41)	(0.41)	(0.41)	

Notes: Sample restricted to +/- 5 window around the cutoff. Personality traits' scores range from 0-7. See notes in Table 2 for variable definitions. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 5: Main results

	Full Sample (1)	Males (2)	Females (3)
Panel A: Cognitive Outcomes			
University exam score	1.121*	-0.737	2.591**
	(0.640)	(1.118)	(1.225)
Observations	2346	1030	1316
Panel B: Behavioral Preferences			
Competitiveness	0.065	0.089	0.081
	(0.095)	(0.117)	(0.092)
Observations	2365	1043	1322
Overconfidence	-0.349**	-0.065	-0.698*
	(0.141)	(0.261)	(0.378)
Observations	2335	1035	1300
Risk preference	3.085	-4.648	12.911***
	(3.632)	(5.411)	(3.568)
Observations	2359	1038	1321
Panel C: Personality Traits			
Extraversion	-0.269*	-0.480**	-0.234
	(0.138)	(0.193)	(0.258)
Observations	2331	1021	1310
Agreeableness	0.031	-0.043	0.026
	(0.099)	(0.171)	(0.229)
Observations	2318	1013	1305
Conscientiousness	-0.254	-0.548***	0.065
	(0.157)	(0.157)	(0.223)
Observations	2340	1029	1311
Emotional stability	0.161	-0.011	0.401
	(0.117)	(0.208)	(0.272)
Observations	2329	1018	1311
Openness to experience	-0.018	-0.031	0.009
	(0.123)	(0.121)	(0.352)
Observations	2328	1018	1310

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 6: Pathways

	Student response			*Teachers*	
	High attendance	Relatively less attendance	External tutorial	Class cancelled	Student-teacher ratio
Panel A: Males					
Enrolled in a selective college	-0.141	0.304***	0.023	0.149	-0.042
	(0.089)	(0.094)	(0.094)	(0.144)	(0.466)
Observations	1043	1043	1043	1043	985
Panel B: Females					
Enrolled in a selective college	0.310***	-0.105	-0.015	-0.036	-0.327
	(0.116)	(0.133)	(0.092)	(0.165)	(0.979)
Observations	1325	1325	1325	1325	1226

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 7: Robustness Checks: Cognitive and Behavioral Outcomes

	University exam score	Behavioral		
		Competitiveness	Overconfidence	Risk preference
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Without controls	1.121	0.068	-0.361**	2.161
	(0.742)	(0.097)	(0.153)	(3.101)
Cubic	1.032	0.091	-0.281	-1.400
	(1.632)	(0.171)	(0.344)	(7.624)
Triangular wt.	0.794	0.078	-0.369***	1.481
	(0.756)	(0.105)	(0.100)	(4.367)
CCT Bandwidth	1.172	0.062	-0.379***	-0.014
	(0.799)	(0.096)	(0.104)	(4.154)
Panel B: Males				
Without controls	-0.552	0.097	-0.070	-5.767
	(1.186)	(0.123)	(0.260)	(5.081)
Cubic	-0.027	0.043	0.306	-4.952
	(1.606)	(0.143)	(0.367)	(6.037)
Triangular wt.	-0.558	0.076	0.020	-6.016
	(1.259)	(0.123)	(0.269)	(5.670)
CCT Bandwidth	-0.380	0.092	-0.007	-4.643
	(1.423)	(0.121)	(0.278)	(5.528)
Panel C: Females				
Without controls	2.404*	0.071	-0.740**	12.211***
	(1.257)	(0.091)	(0.367)	(3.739)
Cubic	5.856	0.542	-4.084	8.218
	(23.598)	(0.924)	(8.053)	(26.605)
Triangular wt.	2.206*	0.146*	-0.980**	13.185***
	(1.279)	(0.079)	(0.469)	(2.997)
CCT Bandwidth	1.877	0.135	-0.774	10.987***
	(2.050)	(0.089)	(0.500)	(3.598)

Notes: All estimates are from instrumental variable regressions using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. CCT bandwidth refers to the optimal bandwidth detailed in Calonico et al. (2014). Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 8: Robustness Checks: Personality Traits

	Big Five				
	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness to experience
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Without controls	-0.258*	-0.009	-0.234	0.117	-0.013
	(0.146)	(0.104)	(0.183)	(0.109)	(0.127)
Cubic	-0.220	0.150	-0.720**	0.353	0.414*
	(0.257)	(0.264)	(0.292)	(0.253)	(0.239)
Triangular wt.	-0.279*	0.059	-0.319***	0.214	0.111
	(0.154)	(0.081)	(0.121)	(0.132)	(0.127)
CCT Bandwidth	-0.100	-0.022	-0.288**	0.144	-0.022
	(0.128)	(0.098)	(0.135)	(0.116)	(0.123)
Panel B: Males					
Without controls	-0.448**	-0.083	-0.466**	-0.126	-0.047
	(0.204)	(0.177)	(0.183)	(0.239)	(0.124)
Cubic	-0.835***	-0.130	-0.546***	-0.068	0.047
	(0.237)	(0.247)	(0.205)	(0.289)	(0.191)
Triangular wt.	-0.678***	-0.085	-0.522***	-0.090	-0.027
	(0.165)	(0.176)	(0.142)	(0.205)	(0.124)
CCT Bandwidth	-0.701***	-0.027	-0.455***	-0.064	-0.104
	(0.204)	(0.203)	(0.172)	(0.222)	(0.134)
Panel C: Females					
Without controls	-0.180	-0.001	0.018	0.375	0.060
	(0.308)	(0.234)	(0.239)	(0.255)	(0.355)
Cubic	2.976	1.407	-1.967	3.032	3.123
	(7.268)	(3.661)	(4.420)	(5.717)	(7.605)
Triangular wt.	0.060	0.175	-0.040	0.701**	0.347
	(0.331)	(0.274)	(0.212)	(0.337)	(0.571)
CCT Bandwidth	0.083	0.024	-0.050	0.814**	0.644
	(0.301)	(0.325)	(0.230)	(0.375)	(0.653)

Notes: All estimates are from instrumental variable regressions using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. CCT bandwidth refers to the optimal bandwidth detailed in Calonico et al. (2014). Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 9: Heterogeneous effects by income and parental education

	University exam score	Behavioral Preferences			Big Five Personality Traits				
		Competitiveness	Overconfidence	Risk preference	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness to experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Males by income									
Enrolled in a selective college	-0.477	0.098	-0.122	-3.526	-0.465**	-0.032	-0.491***	-0.062	-0.036
	(1.101)	(0.119)	(0.258)	(5.174)	(0.207)	(0.171)	(0.152)	(0.208)	(0.125)
Enrolled in a selective college	-0.925	-0.031	0.222*	-4.708*	-0.046	-0.037	-0.216	0.219	0.034
× Low income	(1.132)	(0.060)	(0.114)	(2.855)	(0.170)	(0.148)	(0.154)	(0.162)	(0.124)
Observations	1030	1043	1035	1038	1021	1013	1029	1018	1018
Panel B: Males by parental education									
Enrolled in a selective college	-0.692	0.078	-0.073	-5.269	-0.485**	-0.002	-0.540***	-0.002	-0.030
	(1.249)	(0.122)	(0.268)	(5.393)	(0.203)	(0.172)	(0.155)	(0.215)	(0.119)
Enrolled in a selective college	-0.088	0.049	0.027	2.063	0.029	-0.145	-0.027	-0.003	0.011
× Low parental education	(1.519)	(0.081)	(0.132)	(2.181)	(0.160)	(0.126)	(0.162)	(0.139)	(0.128)
Observations	1030	1043	1035	1038	1021	1013	1029	1018	1018
Panel C: Females by income									
Enrolled in a selective college	2.829**	0.077	-0.727*	10.225***	-0.200	-0.086	-0.011	0.370	-0.004
	(1.285)	(0.094)	(0.391)	(3.479)	(0.272)	(0.216)	(0.231)	(0.270)	(0.342)
Enrolled in a selective college	-0.729	-0.014	0.090	5.592**	-0.034	0.344***	0.184	0.061	0.108
× Low income	(1.042)	(0.058)	(0.136)	(2.446)	(0.137)	(0.132)	(0.131)	(0.119)	(0.147)
Observations	1316	1322	1300	1321	1310	1305	1311	1311	1310
Panel D: Females by parental education									
Enrolled in a selective college	2.678**	0.087	-0.669*	10.504***	-0.230	-0.007	0.033	0.362	0.022
	(1.192)	(0.096)	(0.386)	(3.462)	(0.252)	(0.229)	(0.225)	(0.283)	(0.324)
Enrolled in a selective college	-0.331	-0.047	-0.095	5.116*	0.061	0.100	0.047	0.091	0.030
× Low parental education	(0.997)	(0.056)	(0.147)	(3.018)	(0.124)	(0.162)	(0.162)	(0.140)	(0.149)
Observations	1316	1322	1300	1321	1310	1305	1311	1311	1310

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Panels A and C: eligible for higher quality college × low family income used as an additional instrument. Panels B and D: eligible for higher quality college × low parental education used as an additional instrument. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 10: Heterogeneous effects by college ranks

	University exam score	Behavioral Preferences			Big Five Personality Traits				
		Competitiveness	Overconfidence†	Risk preference	Extraversion	Agreeableness	Conscientiousness	Emotional Stability†	Openness to experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Males in Rank 1									
Enrolled in a selective college	-0.240	-0.197	-0.414***	4.492	-0.365	-0.007	-0.666***	-0.174	-0.412**
	(3.013)	(0.125)	(0.106)	(4.563)	(0.319)	(0.228)	(0.218)	(0.164)	(0.186)
Observations	306	310	307	309	305	303	308	304	304
Panel B: Females in Rank 1									
Enrolled in a selective college	1.189	0.031	-0.315*	9.033**	-0.313	-0.247	0.169	0.062	-0.186
	(1.421)	(0.069)	(0.166)	(3.794)	(0.207)	(0.196)	(0.280)	(0.401)	(0.222)
Observations	494	497	492	497	493	493	494	494	492
Panel C: Males excluding Rank 1 cutoffs									
Enrolled in a selective college	-3.895	0.234	0.945	-17.829	-0.741**	-0.134	-0.239	0.618	0.402
	(3.704)	(0.276)	(0.666)	(14.620)	(0.353)	(0.309)	(0.432)	(0.537)	(0.397)
Observations	724	733	728	729	716	710	721	714	714
Panel D: Females excluding Rank 1 cutoffs									
Enrolled in a selective college	5.823	0.481	-2.079	32.038**	0.476	1.269	-0.047	1.606	0.848
	(4.677)	(0.319)	(1.554)	(16.266)	(0.819)	(1.039)	(0.543)	(1.198)	(1.294)
Observations	822	825	808	824	817	812	817	817	818

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

† : Due to multicollinearity, estimates reported in Panel A are from flexible linear regressions.

Online appendix for:

Cognitive, Socioemotional and Behavioral Returns to College Quality

UTTEEYO DASGUPTA, SUBHA MANI, SMRITI SHARMA, SAURABH SINGHAL

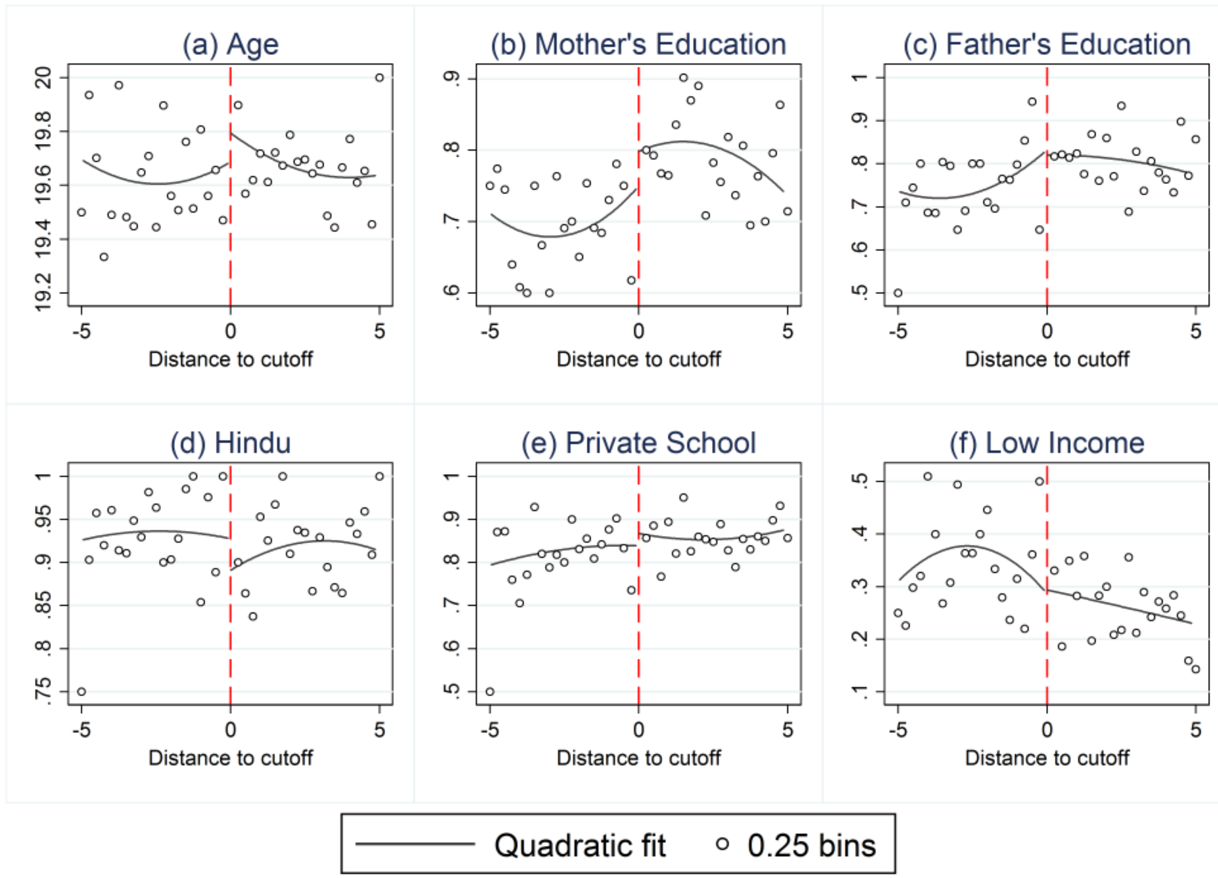

Figure A1: Control Balance: Pooled Sample

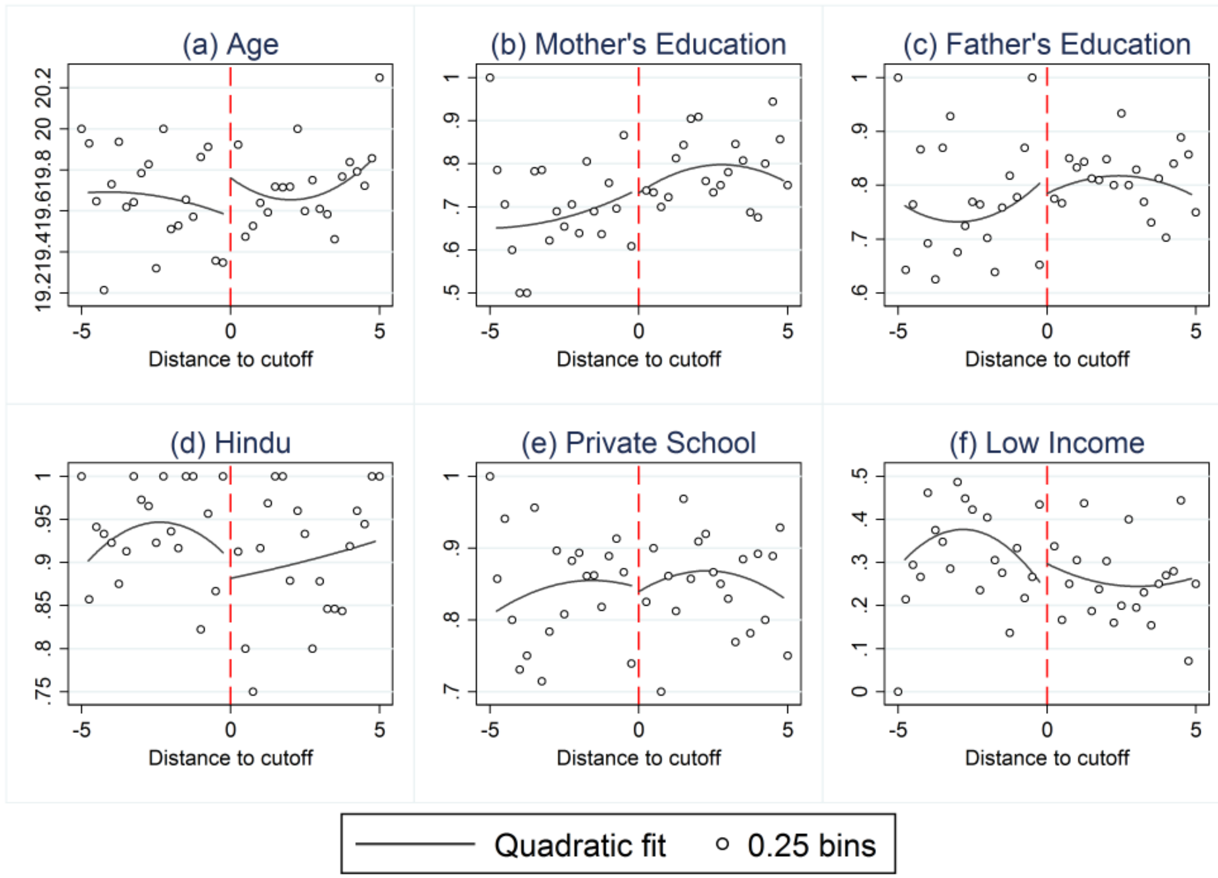

Figure A2: Control Balance: Males

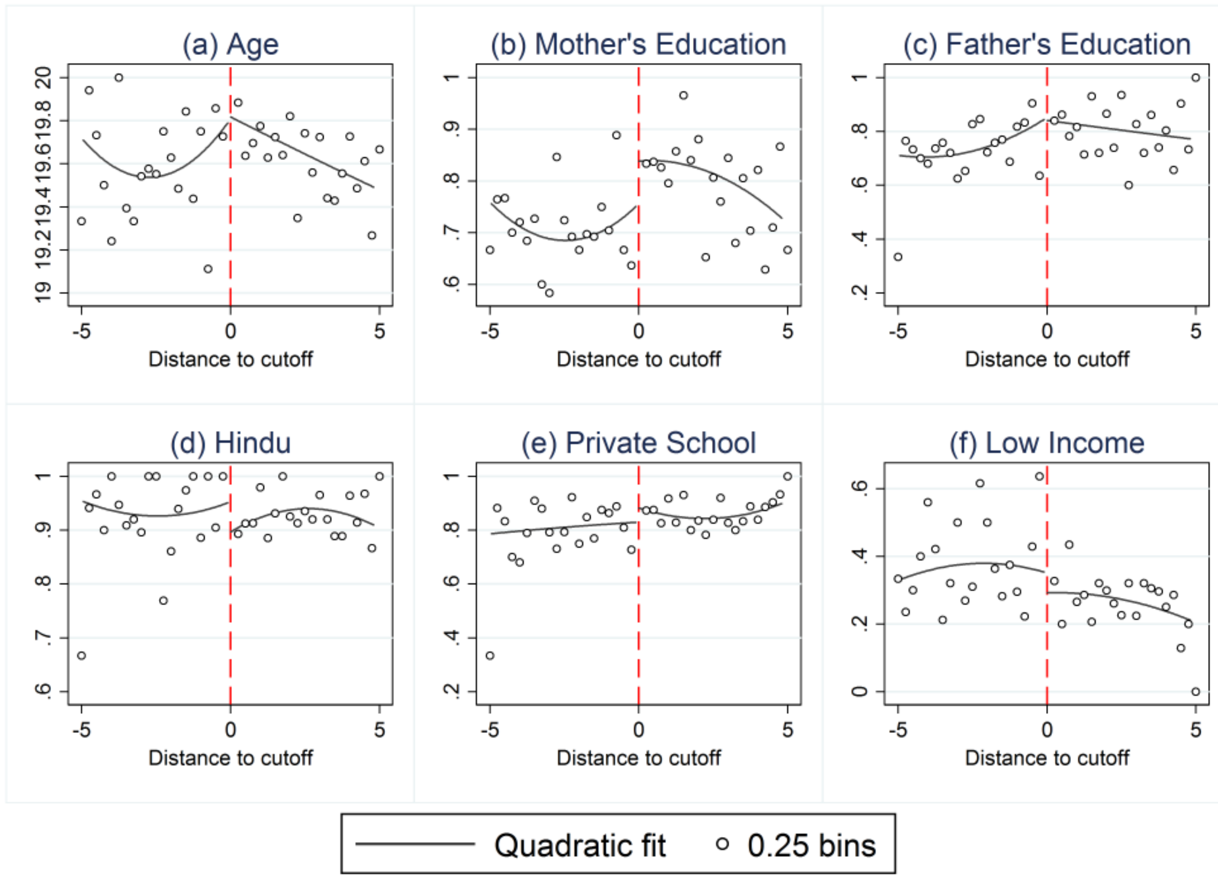

Figure A3: Control Balance: Females

Table A1: Other Variables

	Full Sample (1)	Males (2)	Females (3)
College Societies	-0.189***	-0.282***	-0.129
	(0.073)	(0.103)	(0.087)
Observations	2368	1043	1325
Grit	-0.303	-0.513*	-0.174
	(0.188)	(0.281)	(0.224)
Observations	2278	1011	1267

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A2: Main results: imposing preferences

	Full Sample (1)	Males (2)	Females (3)
Panel A: Cognitive Outcomes			
University exam score	0.484	-0.877	1.131
	(0.922)	(1.669)	(1.412)
Observations	1472	640	832
Panel B: Behavioral Preferences			
Competitiveness	0.061	0.032	0.141*
	(0.093)	(0.130)	(0.078)
Observations	1480	645	835
Overconfidence	-0.402**	-0.186	-0.786*
	(0.179)	(0.330)	(0.468)
Observations	1464	641	823
Risk preference	3.904	-2.305	12.666**
	(2.747)	(4.403)	(5.378)
Observations	1479	642	837
Panel C: Personality Traits			
Extraversion	-0.319	-0.351	-0.512
	(0.245)	(0.290)	(0.395)
Observations	1456	630	826
Agreeableness	-0.089	-0.090	-0.161
	(0.103)	(0.215)	(0.237)
Observations	1454	626	828
Conscientiousness	-0.394**	-0.532***	-0.221
	(0.188)	(0.176)	(0.265)
Observations	1468	638	830
Emotional stability	0.042	-0.063	0.169
	(0.112)	(0.207)	(0.325)
Observations	1463	631	832
Openness to experience	0.056	0.039	0.069
	(0.150)	(0.152)	(0.303)
Observations	1452	627	825

Notes: This table reports instrumental variable estimates using the flexible second order polynomial described in the text. We control for mother's education, father's education, private school enrollment, age, income, and religion in all specifications (see notes in Table 2 for variable definitions). All regressions also include cutoff fixed effects. Standard errors clustered at 0.25 bins of the centered high school exit exam score level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.