Rewarding Schooling Success and Perceived Returns to Education: Evidence from India*

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September 10, 2014

Abstract

This paper tests two specific mechanisms through which individuals can form expectations about returns to investments in education: recognition for schooling performance, and exposure to successful students through family or social networks. Using a regression discontinuity design, we study the impact of two fellowship programs recognizing educational performance in secondary schools in India. We find that the fellowship award is associated with a significant increase in the perceived value of education, by both increasing the perceived mean of earnings (0.74 SD) and decreasing the perceived variance in earnings (1.03 SD) associated with additional years of schooling. The effects spill over only selectively to social and family networks. Peers exposed to successful students do not update their beliefs but parents of fellows report higher perceived returns to education.

Keywords: Returns to Education, Subjective Expectations, Peer Effects
JEL codes: D84; I25; J24

*We are very grateful for the hard work of the survey teams led by Roshan Gupta, Siddhartha Gupta, Enkhtur Maini, Brajesh Pandey, VS Sridhar and the support of Shama Afroz, Sourabh Chakraborty, Udita Das, Reshma Dixit, Mohd. Faheem, Baby Nayak, Preeti Pundir and Pankaj Sharma. We also thank David Atkin, Oriana Bandiera, Pedro Bordalo, Gharad Bryan and Esther Duflo for very thoughtful comments. All errors remain our own.

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1 Introduction

Investments in human capital have long been considered a fundamental part of any sustainable process of economic development and growth (Barro, 1998; Romer, 1989; Mincer, 1974). And yet, despite growing evidence of both the importance of education in the formation of human capital and of high individual returns to schooling (Attanasio and Kaufmann, 2010; Jensen, 2010; Carneiro et al., 2011), demand for education has remained persistently low, particularly among low-income groups in the developing world (Banerjee and Duflo, 2011).

Becker's canonical model (Becker, 1962) of investment in human capital theorizes that demand for education is driven by students' and parents' perception of education as an investment in future income earning capacity: families weight the cost of an additional year of schooling against the perceived benefits accrued by the household in terms of future income. While a growing empirical literature has confirmed the impact of perceived returns to education on schooling decisions (Dominitz and Manski, 1996; Padula and Pistaferri, 2001; Belzil and Hansen, 2002; Nguyen, 2008; Attanasio and Kaufmann, 2009; Jensen, 2010; Attanasio and Kaufmann, 2010), it is also well documented that returns to education are perceived to be low in developing economies (Attanasio and Kaufmann, 2009; Jensen, 2010; Attanasio and Kaufmann, 2010), which could drive down demand for education. The mechanisms through which low perceived returns to education are formed remain, however, poorly understood. Yet, understanding these mechanisms is critical for the design of policies that effectively (and sustainably) increase demand for education in the developing world.

In contrast to the recent literature exploring the impact of providing more accurate information about real returns to education on schooling decisions, this paper examines how perceived returns to education can be endogenously formed in the first place. First, we investigate how being recognized for schooling success affects an individual's perception of future returns to additional years of schooling, where success is evidenced by receiving a fellowship award for academic performance. We then investigate whether exposure to the educational success of others affects one's perceptions of returns to education. We do so by looking at whether changes in perceived returns to education of those rewarded for their schooling performance spill over into their family and social networks. While there is a growing literature documenting the importance of peer effects in schooling behavior in general (Sacerdote, 2001; Kremer and Levy, 2008; Epple and Romano, 2011), the role of peer effects in the formation of perceptions about education remains unexplored.

To analyze the link between rewards for educational performance and perceptions, we measure the impact of two comparable fellowship programs rewarding high performing students in secondary school in India on perceptions of future wages associated with the completion of different levels of schooling. We first designed a survey to examine the impact of recognition on fellows and on those in their networks. We then implemented an extended survey in a different region to validate our main findings and further explore potential mechanisms.

In both settings, we adopt a fuzzy regression discontinuity design to ensure that we are observing a causal relationship between the fellowship award and perceived returns to education. Both fellowships are awarded to students pursuing secondary education in India based on a continuous score that measures each student's academic performance. We exploit a discontinuity in the probability of being awarded the fellowship around a cut-off score defined by the pre-determined budget of the fellowship program. We then take advantage of this same cut-off to identify family and social networks that are exogenously exposed to students who either just made the award criteria or came very close to meeting it.

We present three main findings. First, we show that recognizing students for schooling performance has a significant impact on their perceived returns to investing in additional years of schooling: fellowship recipients perceive that completing higher education relative to lower secondary school can increase monthly entry salaries by an additional 1,369 Rs (\$23[1] or 0.74 SD) in the first five years after graduation. This leads the recipients to have more accurate perceptions of returns to higher education when measured against actual entry-level wages in the marketplace.

Second, fellowship recipients also expect a stronger decrease in the salary variance associated with completing higher levels of education. Recognition for schooling performance lowers the perceived standard deviation of the expected monthly entry salary upon completion of higher education by 1,163 Rs (\$20 or 1.03 SD). Taken together, these two findings show that those rewarded for their schooling performance perceive education as an investment with higher return and lower risk relative to those who achieved similar levels of academic performance but were not rewarded for it.

Third, exposure to successful students recognized for their efforts does not affect the perceived returns to education of friends, neighbors and siblings. We do, however, find that these peers in the network of successful students are 8.4% points more likely to know about sources of funding for secondary education (mean: 27%) and 10.3% points more likely to consider applying for the fellowship itself (mean: 48.7%).

All our main results are confirmed for the fellowship program implemented in a second region in India, which supports the external validity of our findings. The point estimates for the impact of the fellowship on fellows' average expectations are nearly identical for both studies, with an estimated increase in perceived returns of 1,690 Rs (\$28.2) compared to 1,369 Rs (\$23). We provide evidence of the robustness of our results and perform standard tests to validate the identification assumptions underlying our regression discontinuity design.

[1] To facilitate this comparison, we also express the monetary values in US dollar terms (\$) using the exchange rate of \$1 $\approx$ 60 Rs

We also extended the survey in this second study to shed light on the particular mechanisms underlying our main results. In theory, recognition for educational success can directly shape expectations about future earnings through two different mechanisms. In uncertain environments, recognition for educational success can allow an individual to extract a signal about her own skills, or it may change the individual's overall valuation of education, by strengthening the perceived link between schooling effort and rewards. We provide evidence suggesting that the second mechanism is at play. Fellowship recipients are more likely to encourage their peers to apply for the fellowship and also report higher perceived returns to education not only for themselves, but also for others in their cohort.

We also confirm that there is selective transmission of information across networks. While we validate our initial finding on the lack of spill over effects for peers, in the second study we further examine potential spill overs to parents of fellowship recipients. We now find that parents of successful fellows perceive higher expected earnings for additional years of schooling (with a point estimate of 1,162 Rs or $19.4, which is of similar magnitude to that of fellows) and report a higher valuation of education for all of their offspring. This can be important in light of the existing literature documenting how parental beliefs affect investments in education (Nguyen, 2008).

Our results lend further support to studies showing that low-income groups in the developing world underestimate returns to education (Attanasio and Kaufmann, 2010; Kaufmann, 2008; Nguyen, 2008; Jensen, 2010) and that perceptions of risk are important determinants of schooling choices (Kodde, 1986; Altonji, 1993; Padula and Pistaferri, 2001). It departs however from this literature by examining the mechanisms through which perceived returns to education are formed in the first place. Understanding the reverse link of how recognition for educational outcomes affects perceived returns to education matters given that it can reinforce potential unequal investments in education and consequently schooling outcomes across time. Our findings also contribute to a growing literature that identifies the determinants of subjective expectations in the developing world in a variety of contexts. Attanasio et al. (2005) investigate the determinants of subjective expectations of household income in Colombia; Delavande and Kohler (2009) of risk perceptions of HIV/AIDS; Gine et al. (2008) of farmers' expectations regarding the timing of the onset of the monsoon; and McKenzie et al. (2007) of decisions to migrate.

The rest of the paper proceeds as follows: section 2 presents a conceptual framework that will guide the empirical analysis; section 3 discusses the empirical setting and the data used in the study; section 4 presents the analysis and discusses the impact of rewards for performance on perceived returns to education, while section 5 presents our findings on peer effects. Section 6 explores the potential mechanisms through which rewards for educational performance could affect perceived returns to education, section 7 discusses robustness checks and section 8 concludes.

2 Conceptual Framework

2.1 Perceived Returns to Education

In Becker's seminal work on investments in human capital (Becker, 1962), education represents an investment in future income earning capacity. Demand for education can be low if the cost of this investment - both the direct costs of schooling or the indirect costs of foregone income and professional experience - is high or if the returns to it are perceived to be low (Manski, 1993).

In theory, more years of schooling increase the expected level of earnings, but may also affect future income uncertainty (Levhari and Weiss, 1974; Olson et al., 1979; Eaton and Rosen, 1980; Snow and Warren, 1990). To formalize how the returns to education depend on its impact on future earnings, consider an individual i who chooses how much to invest in schooling. The optimal schooling investment s_i maximizes the individual's expected lifetime utility accounting for the (opportunity) cost of schooling,

$$U\left(s_i|\lambda_i,\theta\right)=\Sigma_{k>0}\beta^k E[u(y_{i,k})|s_i,\lambda_i,\theta]-C\left(s_i\right).$$

The individual's distribution of future earnings $y_{i,k}$, conditional on her education, depends on the general quality of education, captured by a parameter θ, and the individual's earning capacity determined by his or her ability and other individual-specific characteristics, captured by λ_i. Individuals form beliefs about both general and individual-specific parameters, and how they affect the distribution of future earnings. To determine an individual's perceived return to additional schooling, it is sufficient to measure gains in perceived expected utility across different levels of schooling. When the expected lifetime utility can be approximated by

$$U\left(s_i|\lambda_i,\theta\right)\cong\Sigma_{k>0}\beta^k\left\{E[y_{i,k}|s_i,\lambda_i,\theta]-\eta_i var[y_{i,k}|s_i,\lambda_i,\theta]\right\}-C\left(s_i\right),$$

the return to additional schooling will only depend on its impact on both the mean and the variance of future earnings, which are the statistics we will focus on in our empirical analysis.[2]

In low-income rural environments, perceptions of returns to education are likely to be formed in contexts of great uncertainty and poor information. Students will often have limited exposure to higher levels of education since parents may not have

[2]This approximation for the expected utility of uncertain earnings corresponds to mean-variance preferences. Note that the approximation is exact when earnings are normally distributed and the individual has CARA preferences with $2\eta_i$ being the parameter of absolute risk aversion. Note also that the (opportunity) cost of schooling is likely to differ across individuals, but our empirical analysis sheds no light on this.

earned an education themselves, and individuals who did tend to migrate to urban areas. Households will also have limited access to information on earnings and unemployment rates for different schooling scenarios given that labor market data are seldom gathered and disseminated in any systematic way.[3] Low income households are therefore more likely to form erroneous beliefs about returns to education, which can then affect their schooling decisions (Attanasio and Kaufmann, 2009; Jensen, 2010).[4] This may result in a vicious cycle in which inaccurate beliefs translate into insufficient investments in education, conditioning labor market outcomes and further reducing perceived returns to education. The end result can pose a great policy challenge of significant heterogeneity and inequality in schooling outcomes, even when, absent variations in the source and type of information available, preferences about schooling trade-offs are similar. In this context, understanding how perceived returns to education are formed in the first place becomes a central theoretical and empirical question.

In this paper we examine the impact of an intervention that sheds light on how perceived returns to education can be endogenously formed. First, we investigate whether being recognized for educational success can directly shape expectations about future earnings associated with different levels of schooling attainment. Second, we examine peer effects as a channel through which expectations of returns to education can be formed, given that peers may form beliefs based on their exposure to the successful

[3] Testing an argument propounded by Wilson (1987) and Jensen (2010) documents how residential segregation can reinforce exposure to different levels and types of information about returns to education due to important selection effects: those living in poor neighborhoods are likely to form erroneous perceptions about the value of education as they are exposed to others with low levels of schooling and to those who, having received schooling, represent the tails of the distribution and have performed poorly in the labor market. The reverse form of selection can occur in high income neighborhoods, reinforcing perceptions about the value of education.

[4] Jensen (2010) finds that a $24 increase in implied perceived returns to secondary education increases the likelihood of returning to school the following year by eight percentage points, and the likelihood of completing high school by nine percentage points. These results are consistent with Kaufmann (2008) and Attanasio and Kaufmann (2009), who find that measures of adolescents' perceived returns are correlated with high school and college enrolment in Mexico.

or unsuccessful outcomes of those in their social and family networks.

2.2 Rewarding Schooling Performance: Direct Effects

In theory, rewards for schooling performance can affect perceived returns to education by providing individual-specific feedback to the students. Students often have imperfect knowledge about their own skills and they will update their beliefs when receiving relevant feedback information: successful students are then expected to revise their beliefs upward, while the unsuccessful students would revise their beliefs downward.[5] If ability and schooling investments are either complements or substitutes, this feedback effect could have a direct impact on future schooling investments. [6]

Besides individual-specific information, the reward can also provide more general information about actual returns to investing in education. In environments of great uncertainty and imperfect information, the recognition may change the beliefs about how schooling effort can be financially rewarding. Since students in the developing world will often underestimate returns to education (Attanasio and Kaufmann, 2009; Jensen, 2010), the reward could potentially reduce this pessimistic bias for successful applicants.

[5] See Azmat and Iriberri (2010) and Bandiera et al. (2012) for a more detailed discussion of this mechanism. These studies investigate the impact of feedback information about school performance, either absolute or relative to others, on their future performance.

[6] Note that the reward may also increase actual returns to education if belonging to a network of fellows enhances income-earning capabilities and employability upon completion of an educational degree. ******can we not say anything more concrete on why this is unlikely? if not I suggest we delete instead of burying it in a footnote.

2.3 Rewarding Schooling Performance: Peer Effects

Motivated by an extensive literature documenting how information obtained through social networks can drive investment decisions (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010), we investigate whether rewarding educational performance affects the perceived returns to education of individuals in the networks of fellowship recipients.[7]

In theory, beliefs about the returns to schooling can potentially be driven by exposure to others experiencing different levels of academic success, and consequently different realized returns to their own investments in education. Understanding how perceptions about returns to education spill over across networks is relevant because it highlights another mechanism through which unequal investments in education could persist - exposure to people with varying degrees of academic success. In our specific context, peer effects can also alter the cost-benefit calculus of the fellowship program itself. The cost-effectiveness of any program that intends to create incentives for students to increase schooling investments is highly dependent on the distribution of direct and indirect treatment effects, including those that reach beyond the immediately targeted group.

The direction of peer effects resulting from exposure to the schooling outcomes of peers is, however, theoretically ambiguous. Observing high-performing role models among those in their network of friends, family or neighbors may lead the agent to revise her beliefs upward on the probability of achieving similar levels of success, but also to revise them downward if peers perceive underlying quality differences relative to the role model (particularly if the level of effort of the role model is difficult to

[7] An important finding from this literature is that the type and size of the social network can determine the extent of social learning. Social learning appears to be maximized when information is transmitted across agents who are most similar in terms of important economic and personal characteristics like gender, income level and ethnicity (Conley and Udry, 2010) or who face similar circumstances (Foster and Rosenzweig, 1995).

observe). Similarly, exposure to unrecognized peers may also either lead to lower perceived returns to education if students learn that effort is not rewarded, or it may motivate students to exert more effort than their peers in order to achieve potential recognition. An additional channel through which peer effects can matter is by determining exposure to general information about education and how to pursue additional years of schooling.

3 Empirical Setting

3.1 Rewards for Schooling Performance

We investigate the impact of education rewards on perceived returns to education in the context of two fellowship programs that reward high-performing students attending secondary education in India. Both fellowship programs are comparable and funded by the same NGO. Our main results are obtained from the first fellowship program, where we collected data in 2011. In 2013, we applied the same research design to the second fellowship program to test the external validity of our initial results, but also to shed additional light on the mechanisms at play, which we discuss in sections 6 and 7 respectively. For expositional purposes, we first focus on the earlier study to explain the empirical setting and to discuss our main results.[8]

The first fellowship program under study was launched in Dehradun district in the state of Uttarakhand in India. The fellowship targets talented girls from disadvantaged backgrounds to encourage them to continue their studies through higher secondary school (hereafter HSC, equivalent to 11th and 12th grades). This is a particularly important demographic group given that higher tuition fees and employability render lack of demand for secondary education particularly acute. Female students

[8]The Appendix A3 contains a detailed discussion of the major differences across both study sites.

may also be less exposed to information about employment opportunities associated with different levels of schooling as they typically lack role models and access to networks of other females entering the labor market.

Our sample covers three waves of eligible applicants for the fellowship program, totaling 570 applicants. The selection process consisted of three stages: the first stage attributed scores to eligible students based on the documentation submitted in their application. Incomplete or poorly documented applications were rejected. The second stage involved a written test, and the third stage consisted of an interview with the candidates and their parents. To ensure that potential candidates did not under-report their income to meet the eligibility criterion, house visits were scheduled for all applicants who passed the third stage; eligibility was then verified using observable proxies for income. The final selection was based on a composite score of the marks given for secondary school, the written test, the interview and the home visit.[9] Successful applicants were awarded Rs 7,000 per annum ($116), paid in four equal installments throughout the year, which were picked up at quarterly workshops held by the NGO. The workshops provided general guidance on study skills and personality development.[10] Unlike the interventions in Jensen (2010) and Nguyen (2008), which provided statistics on the actual returns of schooling, the workshops in our context did not communicate any information about wages associated with different levels of schooling.[11] The fellowship would be withdrawn if students discontinued their studies or if the scholarship was spent for purposes other than education.[12]

[9]See Appendix A1 for a detailed description of the selection process and the construction of the forcing variable.

[10]The most frequent workshop topics focused on improving communication skills, spoken English, problem solving skills and stress management during examinations. The speakers were drawn from the NGO staff or volunteers from local educational institutions.

[11]Note that the second fellowship we examine in this paper did not include workshops.

[12]Only 8 fellowships were withdrawn due to lack of effort or marriage.

3.2 Identification

To measure the effect of the fellowship on perceived returns to education, we adopt a regression discontinuity design (RDD). In our setting, assignment to treatment is determined by the student's score in the selection process relative to a cut-off value. This cut-off was decided by the NGO in charge of the program, based on available funding for each year. While the assignment to treatment does not depend deterministically on the application score, Figure 1 shows a strong discontinuity in the probability of assignment around the cut-off.[13] We exploit this discontinuity as a source of variation to identify the causal relationship between the fellowship award and the outcomes of interest. We adopt a fuzzy regression discontinuity design (FRD), where we flexibly control for the student's score and instrument the fellowship award with whether the student's score exceeds the cut-off value (Lee and Lemieux, 2010; Thistlethwaite and Campbell, 1960; Hahn et al., 2001; Angrist and Lavy, 1999).

[Figure 1 here]

Identification further requires that all relevant factors besides treatment vary smoothly around the cut-off of assignment to treatment (Campbell, 1969). A concern could for example emerge due to selective sorting or manipulation of students' scores close to the cut-off. To directly test for the plausibility of this identifying assumption, Figure 2 plots important baseline characteristics of the applicants such as household size, household income levels and performance in 10th grade as a function of the forcing variable. The forcing variable is centered around the cut-off, marked by a solid vertical line. The dashed lines to either side of it define the sample of comparable students around the cut-off. Figure 2 confirms that all functions are smooth, exhibiting no discontinuities around the cut-off.[14]

[13] This can simply be due to mis-assignment or due to re-assignment by the program administration based on variables that are unobserved by us.

[14] We also conduct placebo regressions that use fictitious cut-offs but we fail to detect any significant treatment effects.

[Figure 2 here]

We apply the same intuition underlying the regression discontinuity design to estimate spill over effects onto the social and family networks of fellowship recipients and non-recipients. We restrict our analysis to peers who are in the networks of students located close to the cut-off point.[15]

To mitigate concerns with endogenous network formation in response to the outcome of the fellowship process, we restrict our sample to networks that were identified as pre-dating the fellowship program. We define peers as including close friends, younger siblings and neighbors. To further mitigate concerns of endogenous network formation, we also examine the younger siblings and neighbors separately as these are unlikely to be formed as a result of the fellowship.

3.3 Data

We conducted three cross-sectional surveys. The main survey targeted a random sample of students drawn from a sampling frame of all students who applied to the fellowship program between 2008 and 2010. To ensure enough observations for the analysis of peer effects, the sample was stratified according to students close to the cut-off and in the remainder group.[16] The 400 students closest to the cut-off were covered. The overall targeted sample size was of 570 students, while the realized sample has 525 students (92%). We do not find any evidence of systematic non-response bias, as evidenced by Table 9. The survey data was supplemented with

[15] Tables 9 and A2 confirm that we fail to reject tests of equality of variable means and distributions at conventional levels when comparing award recipients and non-recipients, and their respective peers, close to the cut-off. These results suggest that targeted recipients and non-recipients, and their peers are indeed comparable. Note that we relax this constraint in the second study to include peers of fellows and non-fellows that are further from the cut-off.

[16] The cut-off value was determined by the score that coincided with the capacity limit in a given batch. The interval of 0.1 score points around the identified cut-off was used to define the restricted sample of applicants with scores close to the cut-off. The remaining observations comprise the rest of the sample.

administrative data, which included the contact details, socio-economic background and application outcome of each applicant.

We conducted a second survey targeting those in the social and family networks of students who were close to the cut-off (both for award recipients and non-recipients). Respondents to the main survey were asked to name, in descending order, three of their closest neighbors, friends and siblings who were female and in grades 8 or 9, thus still eligible to apply for the fellowship and in the process of deciding whether to invest in higher secondary education.[17] We then captured indicators of the frequency with which our respondents interacted with these networks, with a particular focus on the interactions leading to exchanges of information about schooling, jobs and career choices. Our final peer sample (581) was restricted by the fact that both award recipients and non-recipients were often unable to name a close peer: it was only possible to survey 57 siblings as many recipients and non-recipients did not have a sibling in grades 8 or 9. We find, however, no evidence that this constraint varies differentially across networks of recipients and non-recipients (Table 9).

Both surveys collected general information about the student and her peers' socioeconomic and demographic background, as well as detailed information on past schooling and academic performance. To elicit information on perceived returns to education we designed a survey module that captured the individual's perceived distribution of future earnings associated with different levels of schooling. The levels of schooling considered were secondary education (SSC), equivalent to grade 10, higher secondary education (HSC), equivalent to grades 11 and 12, and higher education (HE). The nature of our data allows us to take into account not only average expected returns

[17] Whenever the closest peer was unavailable (after three attempts), the team surveyed the second closest friend. In cases in which the fellows and non-recipients were unable to provide a full list of closest peers either because they lived in remote mountainous areas with few neighbors or because they did not know someone in their network who could still apply, the definition of neighbors and friends was relaxed to include acquaintances. This occurred in approximately 15% of our sample. Our main results remain unchanged when we exclude these cases from the analysis.

but also to derive other moments in the distribution of expected earnings associated with different levels of investments in schooling.[18]

Finally, we conducted an independent audit study to obtain entry level wages in Dehradun district for job seekers with different levels of schooling, among a randomly selected sample of private and public entities in the district. We cross-validated these figures against district-level earnings data collected through India's 61th wave of the NSS (National Sample Survey) conducted in 2004-05. These data are used to evaluate the accuracy of perceived returns to education of fellows and non-recipients.

4 Rewarding Schooling Performance: Direct Effects

4.1 Expected Future Earnings

Our main measure of expected earnings is based on the elicited individual distribution of income earnings for different levels of education. To measure the distribution for individual i, we divide income into the following bins $\mathcal{Y} = \{0 - 5,000; 5,001 - 10,000; 10,001 - 15,000; 15,001 - 20,000; > 20,000\}$. The choice of bin-width was based on the wage distribution of the Indian National Sampling Survey of 2004.

The expected income for a given schooling level s is calculated by weighting each income band (using the lower bound) with its perceived probability $p_i(y_j|s)$[19]:

$$E_i[y|s] = \Sigma_j p_i(y_j|s) \times y_j. \tag{1}$$

[18] See Appendix A2 for a detailed description of the showcards we used to elicit the conditional earnings distributions. Following common practice in the literature, we resorted to visual aids and examples to assist respondents with understanding probabilities prior to answering these expectation questions (Dominitz and Manski, 1996; Attanasio and Kaufmann, 2009; Delavande et al., 2011; Luseno et al., 2003; Lybbert et al., 2004).

[19] The results are robust to alternative definitions of expected income using the upper bound and the midpoint of the income bins (Table A7 of the online appendix).

In Figure 3, we examine the direct effect of the fellowship award on our first measure of perceived returns to education, exploiting the regression discontinuity. Our first measure equals the perceived gain in average earnings from completing higher education (HE) vis-a-vis lower secondary school (SSC),

$$E_i[y|HE] - E_i[y|SSC].$$

After controlling for age, household size, caste, schooling stream and cohort effects, we plot the residuals of this estimation against the forcing variable.[20] We observe a stark increase in perceived returns to completing higher education vis-a-vis lower secondary education at the cut-off point. This increase coincides with the discontinuous jump in the probability of treatment, revealing that the fellowship award shifted perceived returns to higher levels of education.

[Figure 3 here]

To measure the magnitude of the effect, we estimate the following equation:

$$E_i[y|HE] - E_i[y|SSC] = \alpha + \beta \times treatment_i + g(score_i, \boldsymbol{\gamma}) + \boldsymbol{X}_i'\delta + \epsilon_i. \qquad (2)$$

The treatment variable represents a dummy variable indicating the fellowship award; $g(\cdot, \boldsymbol{\gamma})$ is a polynomial function with parameter vector $\boldsymbol{\gamma}$ that controls for the forcing variable and $\boldsymbol{X}_i$ is a vector capturing several control variables such as the age, household size, caste, schooling stream and batch dummies for each wave of the fellowship, for a total of three years of the program. The standard errors are clustered at the school-level to allow for arbitrary correlations of unobservables among students attending the same school.

[20] School streams capture whether students are pursuing their field of specialization in arts, science and commerce.

This equation is first estimated using a sharp regression discontinuity design, where we replace the treatment variable by a dummy for whether the student was above or below the cut-off score, $cutoff_i$ (Table 2, OLS in Panel A). This can be interpreted as our reduced-form estimate of the direct effect. Our preferred estimation, however, uses the fuzzy regression discontinuity design where the treatment variable ($fellow_i$) is instrumented with the dummy $cutoff_i$ (Panel B) to account for the mis-assignment to treatment around the cut-off.

[Table 2 here]

Table 2 confirms the previous graphical results: we detect a statistically significant impact of the fellowship award on the increase in average expected earnings associated with additional schooling. This effect is driven primarily by an increase in the expected wage when completing higher education rather than by a decrease in the expected wage when only completing lower secondary education. The result is robust to the inclusion of an extensive set of individual and family background controls (Panel A, Column 2) and a flexible polynomial function to control for the forcing variable (Columns 3-6). Panel B repeats the same steps for the IV estimates (Columns 7-12). This estimation suggests that the fellowship increases the perceived average gain in expected monthly earnings for obtaining a higher education degree vis-a-vis a secondary schooling degree by 1,369 Rs ($23). This corresponds to an increase in the perceived average gain of completing higher education of about 0.74 standard deviations. This sizable increase in the higher education premium corresponds to about 45% of the average monthly household income of fellowship applicants. The IV estimates are larger than the OLS estimates, consistent with an attenuation bias stemming from imperfect compliance and fuzziness in assignment to treatment.

4.2 Accuracy of Perceived Returns to Education

We analyze how perceived returns of fellowship recipients and rejects compare to actual average returns in the marketplace. To estimate the latter we rely on Mincer earnings regressions (Mincer, 1974; Lemieux, 2006) applied to India's National Sample Survey (NSS) from 2004. We restrict the sample to the state of Uttarakhand where the program is offered and we adjust for inflation using the annual inflation rates between 2004-2008[21].

[Figure 4 here]

Figure 4 compares the estimated coefficients of the difference between perceived and actual returns (unconditional means). The NSS estimate reveals that higher education graduates earn, on average, 3,606 Rs ($60) per month more than SSC graduates. We find that perceived returns to education reported by fellowship recipients are more closely aligned with actual Mincerian returns to education than for non-recipients. We decompose the impact of additional education into the impact of higher education (i.e., HE relative to HSC) and the impact of completing secondary education (i.e., HSC relative to SSC). Comparing HE with HSC, we find that all groups underestimate returns to higher education, but the award of the fellowship appears to reduce this pessimistic bias. Comparing HSC with SSC, we find that both fellowship recipients and non-recipients seem to overestimate returns to having completed secondary education.

Our estimates of perceived returns to education are thus consistent with previous evidence of a pessimistic bias (Attanasio and Kaufmann, 2009; Jensen, 2010). We add the new finding that recognizing educational performance can reduce the gap between perceived and actual returns.

[21]World Bank, World Development Indicators (2013)

4.3 Variance of Expected Future Earnings

Given that our survey elicited the entire earnings distribution, we can also evaluate how the fellowship affects the perceived impact of education on the uncertainty of future earnings. To do so, we construct the standard deviation of perceived future earnings for individual i for a given schooling level s:

$$SD_i[y|s] = \sqrt{\Sigma_j p_i(y_j|s) \times (y_j - E_i[y|s])^2} \tag{3}$$

where $E_i[y|s]$ is the expected perceived wage derived in (1). We analyze the impact of the fellowship award on the difference in standard deviations, $SD_i[y|HE] - SD_i[y|SSC]$, capturing the gain or loss in income variability associated with completing one schooling degree over the other.

[Figure 5 here]

Figure 5 suggests that the fellowship award decreased the variability of perceived future income associated with higher education. This is confirmed by the regression estimates presented in Table 3: while in the total sample the completion of higher education is not expected to have a significant impact on income risk, the fellowship award significantly decreases the standard deviation of expected income gain upon completion of higher education, to a value that is below the standard deviation of expected income associated with secondary education. The magnitude of this difference is also economically significant: the fellowship award decreases the difference in standard deviations by 1,163 Rs ($20). These results are consistent across both OLS (Panel A) and IV (Panel B) specifications.[22]

[Table 3 here]

[22]In Panel C we show that the results are again robust to restricting the analysis to the subset of students with scores close to the cut-off.

Our findings are also robust to alternative measures of dispersion in the distribution of perceived earnings, such as the gap between the probability of the highest expected earnings and the probability of the lowest expected earnings for each level of schooling, $p_i(y_{max}|s) - p_i(y_{min}|s)$ and the inverse of the coefficient of variation, which enables a unit-free comparison across distributions of earnings for each schooling level.[23]

Overall, these results indicate that fellows perceive investments in higher education not only to increase average earnings but also to reduce the variability of their starting salaries.

5 Rewarding Schooling Performance: Peer Effects

In this section we investigate whether changes in perceived returns to education triggered by rewards for academic performance spill over into social and family networks. Figure 6 compares the impact of the fellowship award on the aggregate distribution of perceived returns to education for fellows and their peers. In the left panel, we plot the average difference-in-differences in the perceived probability of ending up in each of the income categories when finishing higher education (HE) relative to lower secondary education (SSC) for recipients and non-recipients, after controlling for a set of individual-level characteristics. The right panel plots the same difference-in-difference results, but for peers of recipients and non-recipients. The left panel suggests that fellowship recipients experience a systematic upward shift in their distribution of perceived returns. That is, fellowship recipients expect that completing higher education has a larger negative effect on the probability of ending up in the lower income bands and a larger positive effect on the probability of ending up in the highest income bands. In contrast to the clear distributional shift for the fellowship

[23]See Tables A3 and Table A4 in the online appendix.

applicants (left panel), we do not find a statistically significant effect for their peers (right panel).

[Figure 6 here]

To further test for peer effects in perceived returns to education, we estimate the following equation:

$$Y_i = \alpha + \beta \times treatment_i + \boldsymbol{X}_i'\delta + \epsilon_i$$

with Y_i equal to $E_i[y|HE] - E_i[y|SSC]$ and $SD_i[y|HE] - SD_i[y|SSC]$ respectively. This sample is restricted to the peers of students with scores around the cut-off so that we cannot exploit the fuzzy discontinuity and flexibly control for the score variable. We relax this in the second study and find similar results when exploiting the discontinuity. Notice also that the restriction to applicants around the cut-off does not affect our estimates of the direct effects either. Since several peers may be exposed to the same fellowship applicants, standard errors are clustered at the level of the applicant.

The regression results confirm the absence of differential spill overs on perceived returns of those among the networks of recipients and non-recipients, measured both by the mean (Table 4, Panel A) and standard deviation (Panel B). Peer effects on perceived mean earnings are never statistically significant. For peer effects on perceived standard deviations, some estimates are marginally significant, but, in contrast to our results for the direct effects of the fellowship on fellows, these estimates are not robust to alternative measures of dispersion in earnings. Moreover, in all cases, the estimated magnitudes are very small relative to the corresponding estimates of the direct effects (see Columns 1-2 and 7-8). To directly test for treatment heterogeneity, we also break down the regressions by network type: endogenous networks of friends and exogenous networks of neighbors and siblings. We fail to detect any statistically significant differential spill over effects on perceived returns across these groups.

[Table 4 here]

5.1 Further Peer Effects

While changes in perceived returns to education do not appear to be transmitted from fellows to their peers, we find systematic evidence of the spilling over of factual information from fellowship recipients to those in their networks (Table 6). In our context, factual information is defined as knowledge about the eligibility criteria and the application process for the fellowship[24] (Columns 1-2), as well as knowledge about funding opportunities other than the fellowship under study (Columns 3-4). We also examine peers' reported intention to apply to the fellowship (Columns 5-6).

Those in the networks of successful applicants scored 5% points higher in the knowledge index, reflecting an improved understanding of the fellowship criteria and application procedures (Column 2).[25] We also find that those in the networks of successful fellows are 11.6% points more likely to know about alternative sources of funding (Column 4). Since knowledge about alternative sources is otherwise very low (with an average score of 27%), this represents a sizable improvement. More importantly, these factual spill overs seem to translate into investment decisions: those exposed to a successful fellow were 14.1% points more likely to consider applying to the fellowship in the subsequent round (Column 6).

Overall, our results suggest that while agents do not update their perceived returns to education when exposed to someone in their network who received a reward for

[24]The variable *knowledge* is defined as the percentage of criteria and application procedures the respondent was able to name unprompted. In our survey, the respondents were asked to identify the three main criteria for eligibility to the fellowship: 1) total income less than 96,000 Rs ($1600) per year, 2) secondary school marks higher than 60%, and 3) admitted to grade 11 at time of application. The three steps involved in the application process that students were asked to identify were: formal application, written test and interview.

[25]When breaking the index down and examining the questions separately, we find that the result is driven by better knowledge about the formal application, the test procedure, the monetary eligibility criteria and the requirement that students need to be admitted to grade 11 at the time of application.

academic performance, they hold higher levels of information regarding the fellowship application process and report a higher intention to apply for it. They are also better informed about alternative sources of funding that could enable them to continue their studies.

6 External validity

We conducted a second study to examine the impact of rewards for schooling performance on perceived returns to education. This allowed us to test the external validity of our findings and to further explore the potential mechanisms driving our results. The second fellowship scheme was implemented in Sambalpur district, state of Orissa, and was comparable to the program in the main study area in Dehradun, state of Uttarakhand. This second fellowship had however the additional advantage of including both boys and girls.[26] We repeated the relevant surveys described in Section 3.3, with an added survey module to elicit parents' beliefs about education. This additional module was motivated by previous studies showing that parents' beliefs about potential earnings associated with additional years of schooling may have a significant impact on their children's investment in education.[27] Finally, we also extended the sample of peers beyond the cut-off to mitigate concerns that our spill over tests in the first study were underpowered.

Table 7 summarizes the main findings for both fellowships and confirms the previous results. For the pooled results including both boys and girls, the point estimate for the effect of the fellowship award is 1,690 Rs ($28.2, Column 4), which is nearly identical

[26]See Appendix A3 for a detailed summary of the eligibility criteria for the Orissa fellowship program and a detailed description of the data collection undertaken for the study.

[27]Nguyen (2008) finds evidence in Madagascar that informing parents about the average income gains from spending one more year in school for children with similar background to their own had a sizable effect on student test scores, particularly for parents who more significantly underestimated returns to education before receiving this information. Jensen (2010) finds similar results among high school students in the Dominican Republic.

to the 1,369 Rs ($22.8) estimated in the first study site (Column 2). While the point estimate for girls only is slightly higher in Orissa (2,173 Rs, $36.2, Column 6), the overall direction and magnitude of the effects appears to be similar across genders. For the standard deviation, we find an effect for girls that is similar in magnitude, but it is no longer significant.[28] Surprisingly, we find no effect for boys.

[Table 7 here]

Despite the larger sample of peers in this second study, we again find no spill over effects for the wage distribution. Since we sampled peers beyond the cutoff in the second study, we can implement the sharp and the fuzzy RDD to estimate these indirect effects. The point estimates are close to zero (see Table 8).

[Table 8 here]

Overall, these results lend strong support to the external validity of our findings.[29] The second study also allows us to more closely examine the mechanisms through which the fellowship award translates into higher perceived returns. We discuss this evidence in the following section.

7 Evidence on Mechanisms

While previous work has established the importance of perceived returns to education for educational investments, our results shed light on the reverse relationship. Students whose achievement in school is recognized expect higher future returns from investing in education: fellowship recipients expect additional years of schooling to

[28]Note that the estimates for girls become significant when we cluster the standard errors at the cohort level rather than the school level. Still, the results are not as robust when considering other dispersion measures, unlike the results in the first study.

[29]This is particularly the case given that the two study sites present some important differences. Orissa is poorer and has lower average levels of education relative to Uttarakhand. The average district-level literacy rate in the main study site (Dehradun, Uttarakhand) is 77% compared to 67% in Sambalpur, Orissa (Census 2011).

both increase their mean earnings and decrease the variance in their earnings. In this section we provide evidence on the mechanisms through which recognition for performance could affect perceived returns to education.

As discussed in section 2.2, the reward could reveal individual-specific information by allowing the applicant to revise beliefs about her ability. However, the reward could also change a student's general view on returns to education, by for example changing beliefs about how schooling effort can be financially rewarding.[30] Distinguishing between these two mechanisms is challenging yet important, as it can determine both the efficiency of additional schooling investments and the potential for spill over effects.[31]

In the following sections we provide suggestive evidence on how the fellowships appear to alter beliefs about the value of education: fellows report higher expected returns to education for themselves but also for others in their cohort, and they are more likely than non-recipients to encourage their peers to apply for fellowships and pursue other sources of funding to continue their studies. We also find that parents of fellows have higher perceived returns to investments in education and are more likely to value education for all of their progeny relative to parents of non-fellowship recipients who exerted the same level of schooling effort, but were not recognized for it.

7.1 Value of Education

If the reward for schooling performance allows fellows to extract a signal about their individual types only, we would not expect them to revise their beliefs about returns to others' education or to encourage their peers to apply for the fellowship. In the sec-

[30]Note that the fellowship is not distributed by the school but by an independent NGO.

[31]Note that we dismiss the possibility that the workshops through which the fellowship installments were distributed in Dehradun were directly conveying information about the wage structure in the marketplace. There were no such workshops associated with the fellowship in Orissa and yet our main results are just as strong.

ond survey in Orissa, we elicited the distribution of wages fellows and non-fellowship recipients expect other students in their cohort to earn upon obtaining different educational degrees. This allows us to test whether the fellowship is interpreted as a signal of individual ability, by introducing a wedge between perceptions of own earning capabilities and those of others.[32] We construct the same measures for the perceived returns to education as described in Section 4.1, but now applied to other students rather than to the respondents themselves.

[Table 9 here]

Table 9 shows that fellows report not only substantially higher returns to education for themselves, but also for others. The magnitude of the estimates is similar. With both sharp (Panel A) and fuzzy RD specifications (Panel B), we fail to detect a statistically significant difference between the expected increase in own earnings and the expected increase in others' earnings at the discontinuity point.[33]

Table 10 reveals that fellowship recipients encourage, on average, 84% more peers to apply to the fellowship relative to non-recipients (Column 1-2). Since those in the networks of fellows and non-recipients are comparable and determined *before* the award, the observed encouragement pattern is once more inconsistent with learning about individual ability. This complements the earlier results that peers of fellows express a stronger intention to apply to the fellowship and are also more likely to be aware of the eligibility criteria and of alternative sources of funding (Tables 4).

[Table 10 here]

[32]The question asked was "Suppose someone from your school completed [Level of schooling]. For each case, what would you expect their monthly salary to be for the first 5 years of their career?"

[33]In the survey conducted in Uttarakhand, respondents were asked to report average sectoral entry salaries for higher education graduates in their cohort. Using these data, we also fail to detect a statistically significant difference between the perceived level of earnings for themselves and for others. However, we did not elicit the full distribution of wages conditional on different education levels in this first study.

In Orissa, our survey elicited further information on the perceived trade off between education and marriage for girls, so as to obtain an indirect measure of the perceived value of education. As further evidence of our proposed mechanism, Table 10 shows that fellowship recipients are more likely to recognize the general trade-off between completing education and early marriage by perceiving it to be more difficult to complete schooling after marriage (Column 3-4), and by reporting a higher optimal age for marriage (Column 5-6).

Taken together, the evidence from both study sites is consistent with the fellowship award sending a signal of the general value of education as a high-return investment. Fellowship recipients will then hold more accurate beliefs as discussed earlier due to their increased optimism about the impact of schooling in general or because they are motivated to seek direct information on wages in the marketplace.

7.2 Selective spill-overs

In Section 5, we documented the selective transmission of information to younger peers who can apply for the fellowship in the future. While we are unable to determine the reasons for this selective transmission, it is possible that information about perceived returns to education is more abstract and harder to accurately convey to peers, relative to actionable information on how to seek fellowships that recognize schooling success. To test if this selective transmission is driven not only by the content of the information but also by the type of recipient, we examine the impact of the fellowship on parental beliefs and attitudes.

[Table 11]

In contrast to younger peers, parents of fellows report higher perceived returns to education, particularly when we account for imperfect compliance using the fuzzy RD

(Table 11, Panel A, Column 1-3). The magnitude of this increase is again comparable to the direct effect on fellows (1,690 Rs ($28.2)). Moreover, parents report higher expectations for all their progeny, not only for the child receiving the fellowship (Panel A, Column 4-6). They do not however report lower perceived dispersion in expected returns (Panel B).

We also find significant shifts in parental attitudes towards education. Parents are more likely to recognize the trade-off between early marriage and completing education (Panel C). While parents of recipients are no more likely to agree or disagree that "all children should pursue the highest education possible" (Column 13-14), they are more likely to agree that their younger children should follow the success of the older ones (Column 15-16) and that children should postpone marriage until they have completed schooling (Column 17-18).

The differential spill over between parents and peers of fellows may result from the fact that the financial award associated with the recognition for schooling performance presents parents with a more salient and tangible benefit from supporting their children's education or that fellows are more likely to discuss future earning capabilities with their parents than with their younger peers. In either case, the increase in the parents' expected returns for both their children and for others is again consistent with an increase in the general valuation of education, as opposed to an update on the individual ability of the child recognized with the fellowship alone.

8 Robustness Checks

In this section we discuss three potential concerns with the robustness of the main results: measurement error in perceived returns to education, manipulation of students' scores and the endogeneity of network formation in the peer effect analysis.

We report robustness checks for both study sites. For expositional purposes, however, we focus the discussion on the first region.

8.1 Social Desirability, Preference Bias and Probabilities

One concern with our results is that our estimates are biased since respondents may have tried to provide the socially desirable response to our survey questions on returns to education.[34] We argue that this is unlikely to be driving our results. First, our survey was conducted by an independent market research team, unrelated to the NGO that was distributing the awards. Moreover, the study was framed as being related to trends in education in the region, as opposed to having any direct link to the specific fellowship program students were participating in. More importantly, to eliminate reporting biases we explicitly avoided direct questions regarding the desirability of education and designed the survey to elicit the perceived returns indirectly through the expected wage distributions conditional on different years of schooling.

A related concern is that students exhibit preference bias, which would lead them to adjust their responses based on schooling decisions they have already made or anticipate to make for other reasons. Our results, however, are based on a direct comparison between students around an arbitrary cut-off so that past schooling efforts are comparable by construction. Moreover, if fellowship recipients are making (or anticipate to make) different schooling investments, this would still have been driven by the fellowship program and its effect on their valuation of education. Again, given the indirect elicitation of perceived returns to education, it seems less plausible that a change in schooling preferences (for some other reason) has affected their beliefs

[34]Note that the direction of this potential bias is unclear: those recognized for their performance may feel the obligation to report a higher valuation of education but those who came close to receiving the fellowship may think that responding positively to a survey could increase their chance of receiving the fellowship in the future. In this case, our results would correspond to the lower bound of the impact of the fellowship program on perceived returns to education.

rather than the other way round.

A further concern with measurement error is that respondents may have a poor understanding of probabilities when computing expected returns. To gauge the respondents' understanding of probabilities, all surveys contained two hypothetical questions where respondents were asked to evaluate the probabilities of drawing a grey and black ball from a bag containing one grey ball and two black balls out of a total of five balls. About 70% of the respondents were unable to consistently provide the correct answer. Our results, however, remain unchanged even when we remove from our analysis the respondents who did not at least recognize the principle of monotonicity, i.e., that because there were more black balls in the bag than grey ones, the probability of selecting a black ball would be higher (see Table A5).[35] Moreover, we were also able to replicate the main findings using reported point estimates for perceived returns which does not demand any knowledge about probabilities (Table A10).

8.2 Manipulation of Scores

In section 3.2 we provide evidence on how potentially relevant factors besides the intervention vary smoothly around the cut-off of assignment to treatment. In Figure 7 we also plot the number of observations in each bin against the midpoints of the bins, to examine whether the distribution of the forcing variable itself is smooth around the cut-off (McCrary, 2008). Even though the actual weights attributed to each of the selection score components - written test, 10th grade marks, interview and income - were unknown to applicants each year, we reject the hypothesis that the density changes smoothly around the cut-off for Uttarakhand, which is suggestive of potential manipulation of the scores around the cut-off.[36] When examining each batch

[35]For Orissa (Panel B), the estimates are no longer significant but the point estimates remain of the same magnitude.

[36]McCrary (2008) proposes a formal test for manipulation around the cut-off by testing for a discontinuity in the density of the forcing variable at the cut-off.

separately, we find that this effect is mainly driven by the third batch of students. For the first two batches, the evidence does not suggest sorting or manipulation of the forcing variable around the cut-off. When we exclude this third batch in which manipulation around the cut-off may have taken place, our results become, however, even stronger. (Tables A8, Panel A). For Orissa, we find no evidence for manipulation around the cut-off (Panel B).

[Figure 7 here]

8.3 Identification of Peer Network

While a commonly used method in the literature, relying on self-reported network data (Conley and Udry, 2010; Bandiera and Rasul, 2006) raises some additional concerns. In both our studies, the realized sample of peers was substantially smaller than our initial targeted sample since many respondents were unable to name a close peer: for example, it was possible to survey only 57 siblings in Uttarakhand as many fellows and non-recipients did not have a sibling in the required age group. This could raise concerns about the extent of systematic non-response bias across networks of fellows and non-fellows, which could in turn bias our estimates. In Table A1, however, we directly test for differences between fellows and non-fellows whose networks we were able to fully sample. We find no evidence of sampling bias. A second concern is that networks may be endogenously generated in response to the outcome of the fellowship process. This would introduce the possibility of reverse causation when assessing the impact of exposure to a fellow on the perceptions of their networks. To mitigate this concern, we restricted the survey to networks that pre-dated the fellowship program.

9 Conclusions

In the developing world, perceptions of returns to education are likely to be formed in contexts of incomplete information: there is often considerable uncertainty and misinformation regarding students' employment prospects and how these prospects vary with different levels of schooling. While recent literature has focused on the provision of information to increase perceived returns to education in the developing world, in this study, we test two important channels that can shed light on how perceptions about returns to education are formed. First, we find that being recognized for schooling performance is strongly associated with higher (and therefore more accurate) expectations of average earnings associated with higher levels of education, but also of less risky jobs and wage profiles relative to students who exerted a similar effort in school but who failed to receive recognition for their efforts. Second, we find no robust evidence that being exposed to those recognized for their schooling performance through networks of friends, neighbors or siblings changes perceived returns to education. This exposure does however lead to enhanced knowledge of sources of funding to support secondary education, to a reported higher intention to apply for the fellowship program in the future and to the ability to accurately identify the factual details of the application process. We also detect significant spill over effects from fellows to their parents, as they report both higher perceived returns to additional years of schooling, a desire to support the education of all their offspring and a more acute perception of the trade off between investing in education and early marriage for girls.

Overall, our findings suggest that financial recognition for schooling performance increases the valuation of the relationship between educational effort and financial reward, and as such may be an important driver of further educational investments. Low-income groups in the developing world often fail to be recognized for their schooling efforts, which can ultimately reinforce unequal investments in education across time. Programs that attempt to recognize students for their performance in school may therefore represent an important policy mechanism to increase students' and parents' valuation of schooling effort in the short run.

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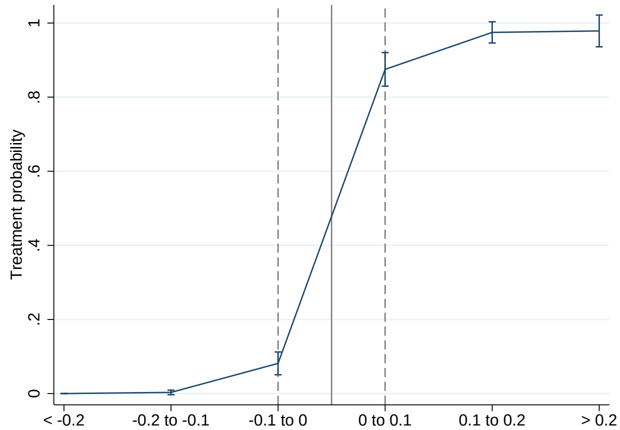

Figure 1: Probability of treatment as a function of the forcing variable, normalized around the cut-off. Solid line indicates the cut-off, dashed lines indicate the sample "close" to the cut-off.

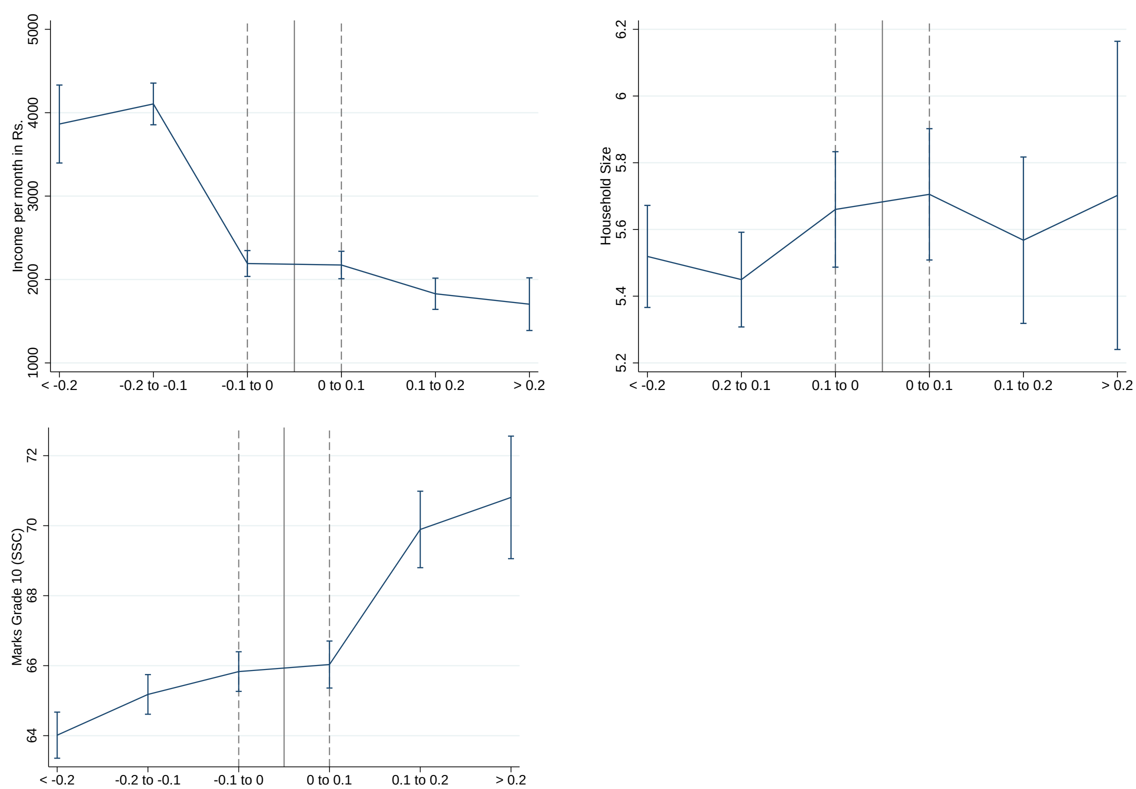

Figure 2: Baseline variables as a function of the forcing variable. Solid line indicates the cut-off, dashed lines indicate the sample "close" to the cut-off.

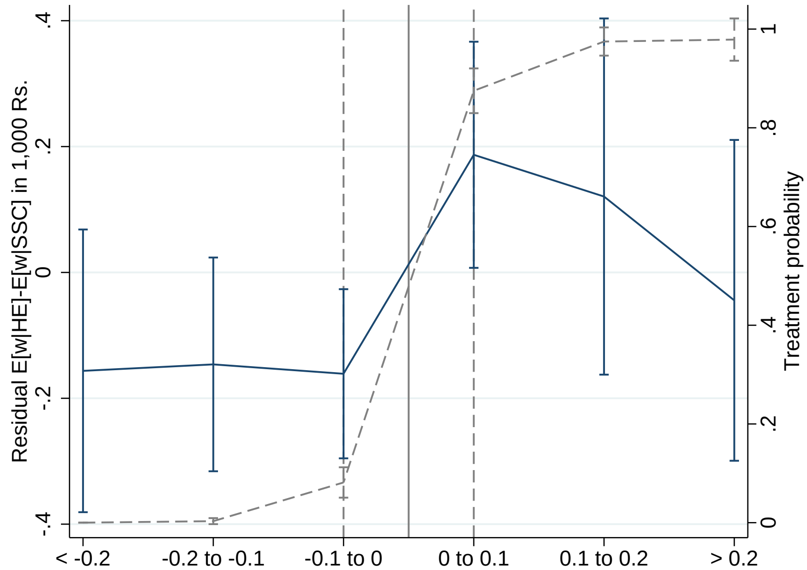

Figure 3: Residual differences (controlling for observables) between perceived average returns to higher (HE) and secondary education (SSC) as a function of the forcing variable. Dashed line shows the treatment probability.

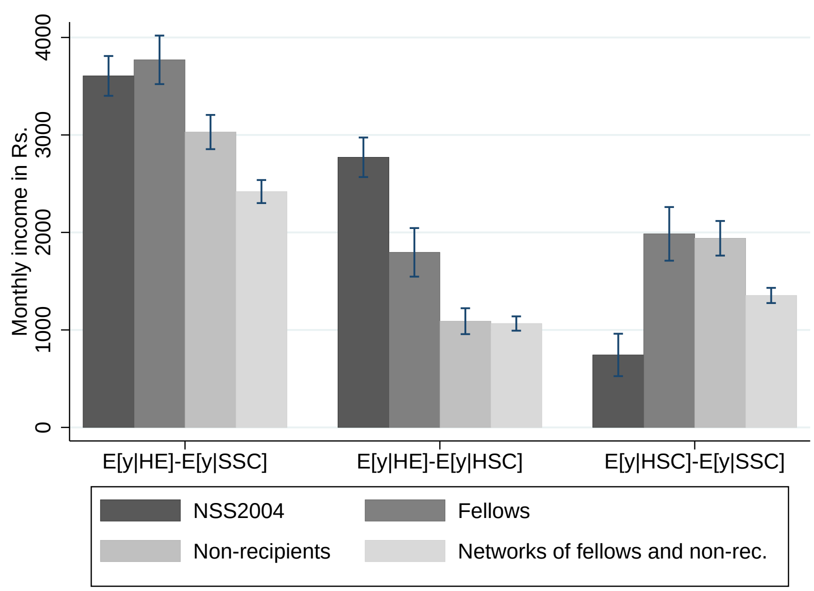

Figure 4: Comparing perceived returns to higher (HE) vs lower secondary education (SSC) with actual Mincerian returns from the Indian National Sample Survey 2004, adjusted for annual inflation between 2004-2008; broken down by perceived gains from higher secondary (HSC) vs lower secondary (SSC) as well as perceived gains from higher (HE) vs higher secondary education (HSC). Figures represent unconditional means.

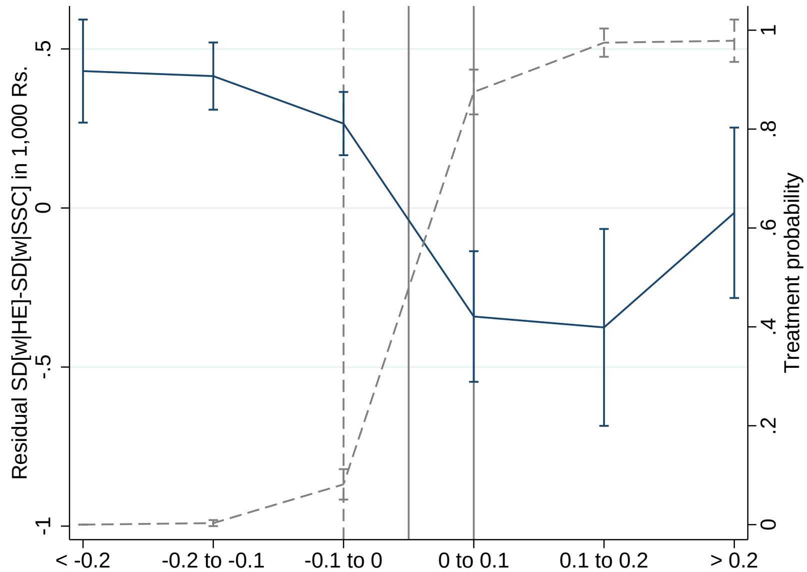

Figure 5: Residual differences (controlling for observables) between the standard deviation in perceived returns to higher (HE) and secondary (SSC) education as a function of the forcing variable. Dashed line shows the treatment probability.

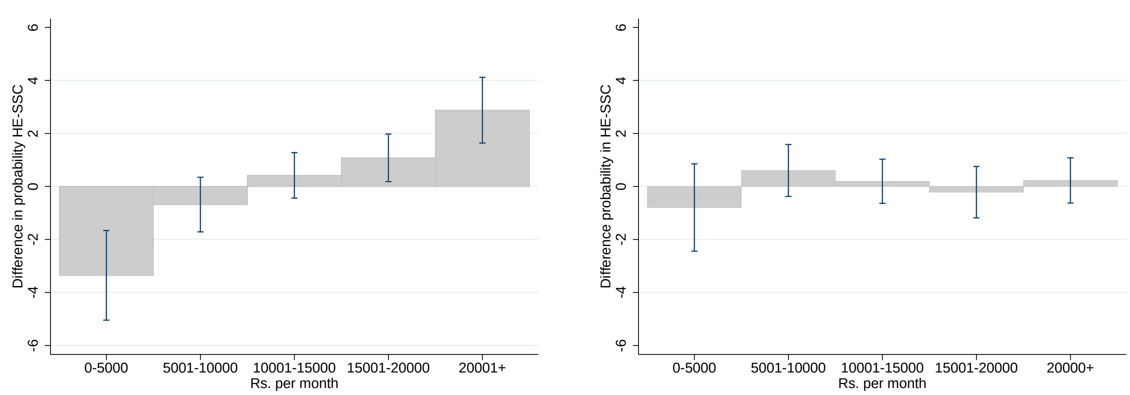

Figure 6: Perceived increase in wage outcomes after completing higher (HE) versus lower secondary education (SSC) for different income bands, after partialling out individual-level characteristics. Left panel corresponds to the direct effect on recipients and non-recipients; right panel shows the indirect effects.

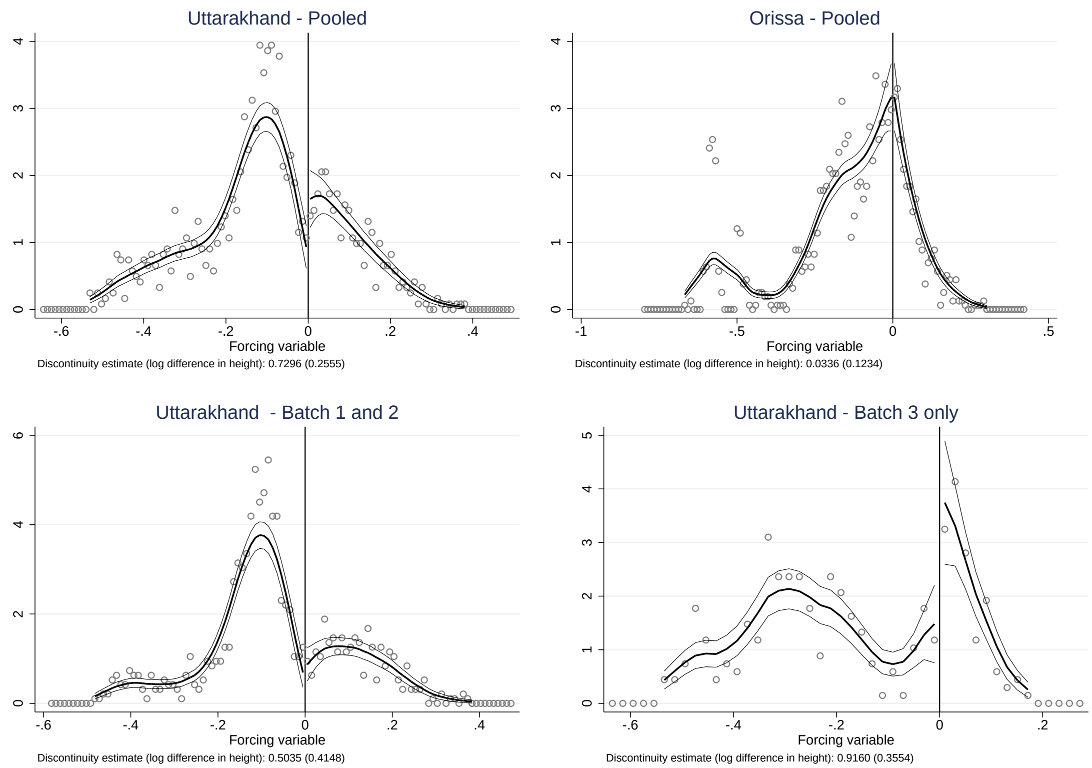

Figure 7: McCrary Test (2008). Testing the null hypothesis of continuity in the density of the forcing variable at the discontinuity point (solid line) for Uttarakhand (top left) and Orissa (top right) studies. The bottom two tests split up the Uttarakhand sample by batch. Standard errors in parentheses.

Table 1: Baseline characteristics of applicants and those in their networks (Uttarakhand)

Panel A: Cut-off sample						**Panel B: Full sample**		
	Applicants			Networks			Applicants	
Batch 1	Treatment	Difference		Treatment	Difference	Batch 1	Treatment	Difference
Grade 10 marks	66.66	0.44	Last year marks	60.493	-1.521	Grade 10 marks	68.68	2.14***
(N=128)	(0.75)	(0.94)	(N=208)	(1.57)	(1.92)	(N=242)	(0.53)	(0.71)
Income month	1968.89	-177.83	Own house	0.80	-0.07	Income month	1948.05	-745.1***
(N=123)	(146.08)	(197.90)	(N=218)	(0.04)	(0.05)	(N=237)	(94.07)	(196.77)
Household size	5.72	0.03	Household size	5.76	-0.13	Household size	5.65	0.06
(N=126)	(0.17)	(0.25)	(N=218)	(0.14)	(0.21)	(N=239)	(0.12)	(0.18)
Batch 2						Batch 2		
Grade 10 marks	65.4	0.47	Last year marks	61.406	1.830	Grade 10 marks	66.18	2.19**
(N=96)	(0.64)	(0.92)	(N=169)	(1.80)	(2.56)	(N=133)	(0.64)	(0.90)
Income month	2620.2	-137.18	Own house	0.85	-0.01	Income month	2347.3	-543.13*
(N=89)	(164.53)	(417.90)	(N=176)	(0.04)	(0.05)	(N=123)	(147.67)	(324.37)
Household size	5.36	-0.12	Household size	6.00	0.28	Household size	5.42	0.03
(N=96)	(0.21)	(0.32)	(N=176)	(0.14)	(0.22)	(N=133)	(0.18)	(0.26)
Batch 3						Batch 3		
Grade 10 marks	64.84	-0.74	Last year marks	62.148	-0.177	Grade 10 marks	65.8	0.80
(N=94)	(0.45)	(1.33)	(N=170)	(1.41)	(2.46)	(N=148)	(0.51)	(0.84)
Income month	2633.71	156.21	Own house	0.75	0.04	Income month	2539.2	-405.49
(N=86)	(147.44)	(555.22)	(N=181)	(0.03)	(0.07)	(N=137)	(143.57)	(315.38)
Household size	5.68	0.12	Household size	6.03	0.49**	Household size	5.74	0.11
(N=94)	(0.17)	(0.31)	(N=181)	(0.15)	(0.22)	(N=148)	(0.16)	(0.22)
Pooled						Pooled		
Grade 10 marks	65.53	-0.22	Last year marks	61.466	0.099	Grade 10 marks	67.21	1.76***
(N=318)	(0.34)	(0.54)	(N=547)	(0.92)	(1.26)	(N=523)	(0.33)	(0.47)
Income month	2440.49	81.52	Own house	0.79	-0.04	Income month	2214.2	-594.5***
(N=298)	(91.31)	(177.48)	(N=575)	(0.02)	(0.03)	(N=497)	(71.73)	(150.91)
Household size	5.59	-0.01	Household size	5.94	0.17	Household size	5.62	0.07
(N=316)	(0.10)	(0.17)	(N=575)	(0.08)	(0.13)	(N=520)	(0.08)	(0.12)

Notes: Balance test for fellows and non-recipients (applicants) and those in their networks (networks) for the cut-off sample (Panel A) and the full sample (Panel B). Column *treatment* shows the means for the fellows and the column *Difference* shows the difference in means between fellows and non-recipients. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Testing for balanced sample between

fellows and non-recipients around the cut-off and across the full sample (Uttarakhand)

Panel A: Respondents around cut-off				Panel B: All Respondents			
Batch 1	Fellows (1)	Non-recipients (2)	Diff (1)-(2)		Fellows (3)	Non-recipients (4)	Diff (3)-(4)
Grade 10 marks	66.66	66.22	0.44	Grade 10 marks	68.68	66.53	2.14***
(N=128)	(0.75)	(0.56)	(0.94)	(N=242)	(0.53)	(0.48)	(0.71)
Income month	1968.89	2146.73	-177.83	Income month	1948.05	2693.23	-745.1***
(N=123)	(146.08)	(133.50)	(197.90)	(N=237)	(94.07)	(172.83)	(196.77)
Household size	5.72	5.68	0.03	Household size	5.65	5.59	0.06
(N=126)	(0.17)	(0.18)	(0.25)	(N=239)	(0.12)	(0.14)	(0.18)
Batch 2							
Grade 10 marks	65.4	64.92	0.47	Grade 10 marks	66.18	63.98	2.19**
(N=96)	(0.64)	(0.66)	(0.92)	(N=133)	(0.64)	(0.62)	(0.90)
Income month	2620.2	2757.38	-137.18	Income month	2347.3	2890.4	-543.13*
(N=89)	(164.53)	(384.15)	(417.90)	(N=123)	(147.67)	(288.80)	(324.37)
Household size	5.36	5.48	-0.12	Household size	5.42	5.38	0.03
(N=96)	(0.21)	(0.24)	(0.32)	(N=133)	(0.18)	(0.19)	(0.26)
Batch 3							
Grade 10 marks	64.84	65.59	-0.74	Grade 10 marks	65.8	64.99	0.80
(N=94)	(0.45)	(1.25)	(1.33)	(N=148)	(0.51)	(0.66)	(0.84)
Income month	2633.71	2477.5	156.21	Income month	2539.2	2944.7	-405.49
(N=86)	(147.44)	(535.28)	(555.22)	(N=137)	(143.57)	(280.80)	(315.38)
Household size	5.68	5.56	0.12	Household size	5.74	5.62	0.11
(N=94)	(0.17)	(0.25)	(0.31)	(N=148)	(0.16)	(0.15)	(0.22)
Pooled							
Grade 10 marks	65.53	65.75	-0.22	Grade 10 marks	67.21	65.45	1.76***
(N=318)	(0.34)	(0.42)	(0.54)	(N=523)	(0.33)	(0.33)	(0.47)
Income month	2440.49	2358.96	81.52	Income month	2214.2	2808.8	-594.5***
(N=298)	(91.31)	(152.18)	(177.48)	(N=497)	(71.73)	(132.77)	(150.91)
Household size	5.59	5.60	-0.01	Household size	5.62	5.55	0.07
(N=316)	(0.10)	(0.12)	(0.17)	(N=520)	(0.08)	(0.09)	(0.12)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Direct impact of fellowship reward on perceived returns (Uttarakhand)

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	3.424	3.422	3.422	3.422	3.422	3.422
$cutoff$	0.562***	0.541***	0.744***	0.741***	0.706***	0.759***
	(0.13)	(0.13)	(0.24)	(0.24)	(0.24)	(0.26)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Sharp	Sharp	Sharp	Sharp	Sharp
Observations	514	512	512	512	512	512
R^2	0.02	0.06	0.06	0.06	0.07	0.07
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	3.424	3.422	3.422	3.422	3.422	3.422
$fellow$	0.673***	0.647***	1.275***	1.258***	1.232***	1.369***
	(0.17)	(0.16)	(0.44)	(0.45)	(0.45)	(0.49)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	514	512	512	512	512	512
R^2	0.04	0.08	0.09	0.10	0.10	0.10

Notes: The direct impact of the fellowship award on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. **Panel A** shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable taking the value 1 if the student is above the cut-off and 0 otherwise, with control variables and a flexible functional form for the forcing variable. **Panel B** shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$.The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Fellowship and standard deviation of perceived returns (Uttarakhand)

	Dependent variable: $SD_i[y \mid HE] - SD_i[y \mid SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	-0.169	-0.169	-0.169	-0.169	-0.169	-0.169
$cutoff$	-0.653***	-0.659***	-0.631***	-0.643***	-0.634***	-0.645***
	(0.06)	(0.06)	(0.17)	(0.17)	(0.17)	(0.18)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.09	0.13	0.13	0.13	0.13	0.13
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.169	-0.169	-0.169	-0.169	-0.169	-0.169
$fellow$	-0.782***	-0.788***	-1.081***	-1.093***	-1.107***	-1.163***
	(0.08)	(0.08)	(0.23)	(0.23)	(0.24)	(0.28)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.13	0.17	0.17	0.17	0.17	0.17

Notes: The direct impact of the fellowship award on the standard deviation (SD) of perceived returns, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $SD_i[y|HE]$ and $SD_i[y|SSC]$ in 1,000 Rs ($16). **Panel A** shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that takes the value 1 if the student is above the cut-off and 0 otherwise, including control variables and allowing the forcing variable to take a flexible functional form. **Panel B** shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Peer effects on perceived returns of those in the networks - Cutoff sample (Uttarakhand)

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Direct (Applicants)		Indirect (Networks)			
	Applicants		Pooled		Friends	Exogenous
Mean of dep. variable	3.498	3.498	2.419	2.419	2.416	2.421
$cutoff$	0.682***	0.697***	0.124	0.185	0.140	0.140
$(fellow)$	(0.18)	(0.19)	(0.14)	(0.14)	(0.18)	(0.18)
Forcing variable	No	No	No	No	No	No
Controls	No	Yes	No	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	313	312	575	575	262	313
R^2	0.03	0.08	0.00	0.06	0.06	0.09
Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$						
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Direct (Applicants)		Indirect (Networks)			
	Applicants		Pooled		Friends	Exogenous
Mean of dep. variable	-0.169	-0.169	1.089	1.089	1.117	1.066
$cutoff$	-0.782***	-0.788***	0.173	0.218*	0.267*	0.173
$(fellow)$	(0.08)	(0.08)	(0.12)	(0.12)	(0.15)	(0.15)
Forcing variable	No	No	No	No	No	No
Controls	No	Yes	No	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	514	512	575	575	262	313
R^2	0.13	0.17	0.00	0.07	0.09	0.07

Notes: Peer effects of exposure to recipients vs. non-recipients on the perceived returns (mean and SD) of those in the networks. For comparison, Column (1)-(2) and Column (7)-(8) report OLS estimates of the direct impact of the fellowship on recipients vs. non-recipients (Table 2 and Table 3) estimated around the cut-off, with and without controls. **Panel A:** Pooled effect on perceived returns of those in the networks of fellows around the cut-off, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$ of peers around the cut-off, with and without controls. Column (3)-(6) repeat the estimation for the indirect effect around the cut-off. **Panel B:** Pooled effects on the standard deviation (SD) of perceived returns of those in the networks of fellows around the cut-off ($SD_i[y|HE] - SD_i[y|SSC]$). Column (9)-(12) repeat the estimation for the indirect effects on the SD around the cut-off. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Column (5) and Column (11) confine the sample to only friends and Column (6) and Column (12) only on exogenously determined peers, siblings and neighbors. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipients). *** $p < 0.01$. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Peer effects on factual knowledge about fellowship and intention to apply in the networks - Cutoff sample (Uttarakhand)

Further outcomes: Knowledge and intention to apply						
	(1)	(2)	(3)	(4)	(5)	(6)
			Indirect (Networks)			
	Knowledge fellowship		Knows funding		Plans to apply	
Mean of dep. variable	0.195	0.195	0.270	0.270	0.487	0.487
$cutoff$	0.047***	0.036**	0.095***	0.084***	0.139***	0.103**
	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)	(0.04)
Forcing variable	No	No	No	No	No	No
Controls	No	Yes	No	Yes	No	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	575	575	575	575	575	575
R^2	0.01	0.14	0.01	0.40	0.01	0.15

Notes: Peer effects of exposure to recipients vs. non-recipient on measures of knowledge about the fellowship and intention to apply. Knowledge about the fellowship is measured by a composite score between 0 (lowest) and 1 (highest) and estimated around the cut-off, with and without controls (Column (1)-(2)). Column (3)-(4) estimate the effects on whether the peer knows at least one alternative source of funding (other than the fellowship under study). Column (5)-(6) report the effect on intention to apply to the fellowship. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). *** $p < 0.01$. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Peer effects on perceived returns (SD) of those in the networks (Uttarakhand)

Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$				
Panel A	(1)	(2)	(3)	(4)
	OLS		IV	
Mean of dep. variable	1.089	1.089	1.089	1.089
$cutoff$	0.137	0.159*	0.183	0.218*
$(fellow)$	(0.09)	(0.09)	(0.12)	(0.12)
Forcing variable	No	No	No	No
Controls	No	Yes	No	Yes
Observations	575	575	575	575
R^2	0.00	0.08	0.00	0.07
Panel B	(5)	(6)	(7)	(8)
	Indirect effect, broken down by network			
	Siblings & Neighbors		Friends	
	OLS	IV	OLS	IV
Mean of dep. variable	1.066	1.066	1.117	1.117
$cutoff$	0.123	0.173	0.200*	0.267*
$(fellow)$	(0.11)	(0.15)	(0.11)	(0.15)
Controls	Yes	Yes	Yes	Yes
Observations	313	313	262	262
R^2	0.07	0.07	0.10	0.09

Notes: Pooled effects on the standard deviation of the perceived returns of fellows around the cut-off, as measured by the difference between $SD_i[y|HE]$ and $SD_i[y|SSC]$ in 1,000 Rs ($16) of peers around the cut-off, with and without controls (**Panel A**). Column (1)-(2) report OLS estimates while Column (3)-(4) report IV estimates where selection is instrumented by $cutoff$. **Panel B** reports the peer effects broken down by network type, with and without controls. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). In 1,000 Rs ($16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: External validity - Direct results across both study sites

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Uttarakhand (Site I)		Orissa (Site II)			
	Girls only		Full sample		Girls only	
Mean dep. var.	3.422	3.422	5.372	5.372	5.215	5.215
$cutoff$	0.759***	1.369***	0.682**	1.690**	1.015*	2.173**
$(fellow)$	(0.26)	(0.49)	(0.34)	(0.80)	(0.58)	(1.08)
Forcing	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Fuzzy	Sharp	Fuzzy	Sharp	Fuzzy
Observations	512	512	550	550	265	265
R^2	0.070	0.100	0.187	0.198	0.240	0.247
	Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$					
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Uttarakhand (Site I)		Orissa (Site II)			
	Girls only		Full sample		Girls only	
Mean dep. var.	-0.169	-0.169	1.796	1.796	1.853	1.853
$cutoff$	-0.645***	-1.163***	-0.061	-0.151	-0.322	-0.690
$(fellow)$	(0.18)	(0.28)	(0.20)	(0.47)	(0.30)	(0.60)
Forcing	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Fuzzy	Sharp	Fuzzy	Sharp	Fuzzy
Observations	512	512	550	550	265	265
R^2	0.130	0.170	0.205	0.205	0.308	0.272

Notes: Comparing the effect of the fellowship on perceived returns to education (mean and SD) across Uttarakhand Site and Orissa Site. The program effect is estimated using the same empirical strategy and specification (See Section 4.1 and 4.2). **Panel A** shows the effect of the fellowship on expected returns from completing higher education (HE) vis-a-vis lower secondary school (SSC). **Panel B** shows the standard deviation of the expected returns. *treat* is a dummy variable that indicates whether the student is above or below the cut-off (Sharp RDD) or the actual treatment instrumented by the cut-off (Fuzzy RDD). All specifications use quartic polynomials to flexibly control for the forcing variable. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. In 1,000 Rs ($16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: External validity - Peer effects on perceived returns of those in the networks

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Uttarakhand (Site I)		Orissa (Site II)			
	Girls only		Full sample		Girls only	
Mean of dep. variable	2.419	2.419	5.281	5.281	5.314	5.314
$cutoff$	0.185	0.255	0.077	0.198	-0.081	-0.169
$(fellow)$	(0.14)	(0.19)	(0.27)	(0.67)	(0.35)	(0.69)
Forcing variable	No	No	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Fuzzy	Sharp	Fuzzy	Sharp	Fuzzy
Observations	575	575	887	887	416	416
R^2	0.07	0.06	0.200	0.202	0.248	0.247
	Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$					
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Uttarakhand (Site I)		Orissa (Site II)			
	Girls only		Full sample		Girls only	
Mean of dep. variable	0.195	0.195	1.980	1.980	1.927	1.927
$cutoff$	0.159*	0.218*	0.006	0.014	0.065	0.137
	(0.09)	(0.12)	(0.12)	(0.31)	(0.21)	(0.42)
Forcing variable	No	No	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Fuzzy	Sharp	Fuzzy	Sharp	Fuzzy
Observations	575	575	887	887	416	416
R^2	0.08	0.07	0.227	0.226	0.267	0.265

Notes: Comparing the peer effects on perceived returns to education (mean and SD) across Uttarakhand Site and Orissa Site. The program effect is estimated using the same empirical strategy and specification. **Panel A** reports the peer effects of exposure to recipients vs. non-recipient on perceived returns of fellows around the cut-off, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. **Panel B** repeats the estimation using the standard deviation in perceived returns $SD_i[y|HE] - SD_i[y|SSC]$. $treat$ is a dummy variable that indicates whether the student is above or below the cut-off (Sharp RDD) or the actual treatment instrumented by the cut-off (Fuzzy RDD). For Uttarakhand, the sample is confined to around the cut-off. Orissa includes the full sample and uses quartic polynomials to flexibly control for the forcing variable. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. In 1,000 Rs ($16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Direct impact of fellowship reward on perceived returns for others (Orissa)

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
	Own expected wage			Expected wage for others		
Mean dep. var.	5.372	5.372	5.372	5.375	5.375	5.375
$cutoff$	0.347	0.402	0.682**	0.340	0.517*	0.738**
	(0.26)	(0.31)	(0.34)	(0.25)	(0.30)	(0.33)
Forcing variable	No	Linear	Quartic	No	Linear	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Sharp	Sharp	Sharp	Sharp	Sharp	Sharp
Observations	550	550	550	550	550	550
R^2	0.177	0.177	0.187	0.203	0.204	0.211
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
	Own expected wage			Expected wage for others		
Mean dep. var.	5.372	5.372	5.372	5.375	5.375	5.375
$fellow$	0.528	0.805	1.690**	0.517	1.036*	1.829**
	(0.38)	(0.59)	(0.80)	(0.36)	(0.57)	(0.81)
Forcing variable	No	Linear	Quartic	No	Linear	Quartic
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R^2	0.183	0.186	0.198	0.207	0.212	0.216

Notes: The direct impact of the fellowship award on perceived returns to education for others in the Orissa Site, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. **Panel A** shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable taking the value 1 if the student is above the cut-off and 0 otherwise, with control variables and a flexible functional form for the forcing variable. **Panel B** shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C breaks down the sample by gender of the role model. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Peer effects on encouragement and attitudes towards schooling/marriage in the networks of recipients/non-recipients (Orissa)

Further outcomes: Encouragement and attitudes						
	(1)	(2)	(3)	(4)	(5)	(6)
	Encouraged		School after marriage		Marriage age	
Mean of dep. variable	1.028	1.028	0.490	0.490	26.061	26.061
$fellow$	0.787**	0.847***	-0.069**	-0.087**	1.107***	0.924
	(0.16)	(0.20)	(0.03)	(0.04)	(0.45)	(0.66)
Forcing variable	Linear	Quartic	Linear	Quartic	Linear	Quartic
Controls	No	Yes	No	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	550	550	550	550	550	550
R^2	0.305	0.313	0.144	0.155	0.389	0.393

Notes: Effect of the fellowship reward on further outcomes for recipients vs. non-recipients in the Orissa Site. The dependent variable is (log) number of others encouraged to apply for the fellowship (Column (1)-(2)), agreeing whether ”it is easy to continue schooling after marriage” (Column (3)-(4)) and the preferred age for own marriage (Column (5)-(6)). The $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Spill-overs on perceived returns (mean and SD) for parents (Orissa)

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Expectation own child			Other children		
Mean of dep. variable	4.881	4.881	4.881	5.128	5.128	5.128
$fellow$	0.854***	1.257***	1.255***	1.123***	1.672***	2.026***
	(0.28)	(0.26)	(0.27)	(0.22)	(0.29)	(0.65)
Forcing variable	No	Linear	Quartic	No	Linear	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	423	423	423	443	443	443
R^2	0.322	0.320	0.328	0.304	0.296	0.301
	Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$					
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Expectation own child			Other children		
Mean of dep. variable	1.888	1.888	1.888	1.913	1.913	1.913
$fellow$	0.224	0.436	0.931**	0.110	0.362	0.826**
	(0.18)	(0.33)	(0.38)	(0.21)	(0.38)	(0.41)
Forcing variable	No	Linear	Quartic	No	Linear	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	423	423	423	423	443	443
R^2	0.139	0.136	0.119	0.155	0.157	0.163
	Indirect outcomes on parental attitudes to education					
Panel C	(13)	(14)	(15)	(16)	(17)	(18)
	Education for all		Role model		Delay marriage	
Mean of dep. variable	0.720	0.720	0.645	0.645	0.586	0.586
$cutoff$	0.026	0.026	0.091***	0.150***	0.065***	0.061***
$(fellow)$	(0.04)	(0.07)	(0.01)	(0.04)	(0.01)	(0.02)
Forcing variable	Linear	Quartic	Linear	Quartic	Linear	Quartic
Controls	No	Yes	No	Yes	No	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Observations	443	443	443	443	443	443
R^2	0.301	0.302	0.271	0.263	0.350	0.351

Notes: The indirect impact of the fellowship award on perceived returns of parents in the Orissa Site for own children and children of others, as measured in change in mean $E_i[y|HE] - E_i[y|SSC]$ (**Panel A**) and SD $SD_i[y|HE] - SD_i[y|SSC]$ (**Panel B**), in 1,000 Rs ($16). As a reference, Column (1)-(2) and (7)-(8) report the direct effect for the full sample. **Panel C:** Effect of the fellowship reward on attitudes of parents of recipients vs. non-recipients. The dependent variable is "All my children should follow the highest education possible" (0: disagree, 1: agree) in Column (13)-(14), "If the oldest child is successful in school, the younger children should follow" (Column (15)-(16)) and "My children should postpone marriage until they have completed their education" (Column (17)-(18)). All spcifications use a fuzzy regression discontinuity design, where the actual fellowship award is instrumented using the cut-off. The unit of observation is the student. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Online appendix: Robustness checks - Not for publication

Table A1: Baseline characteristics of planned and realized sample

	Planned sample (1)	Actual Sample (2)	Diff (1)-(2)
Panel A: Pooled Uttarakhand			
Grade 10 marks	66.03	66.42	-0.38
(N=1095)	(0.22)	(0.24)	(0.33)
Income month	2473.22	2477.96	-4.74
(N=1043)	(68.20)	(72.24)	(99.35)
Household size	5.63	5.58	0.04
(N=1090)	(0.06)	(0.06)	(0.08)
Panel B: Pooled Orissa			
Grade 10 marks	73.35	71.71	1.64***
(N=1593)	(0.40)	(0.29)	(0.50)
Income month	3310.56	3178.54	132.01
(N=1609)	(77.28)	(74.92)	(107.64)

Notes: Testing for non-response bias in the recipients/non-recipients sample for both study sites. Showing differences in baseline characteristics between planned and realized sample: pooled and broken down by batches. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Testing equality of distributions in baseline variables

	Testing for equality of distributions	
p-values	Cut-off (1)	All respondents (2)
Panel A: Pooled Uttarakhand		
Grade 10 marks	0.735	0.007***
(N=523)		
Income month	0.146	0.016**
(N=497)		
Household size	0.998	0.979
(N=520)		
Panel B: Pooled Orissa		
Grade 10 marks	0.902	0.000***
(N=544)		
Income month	0.347	0.329
(N=548)		

Notes: Kolmogorov-Smirnov Test for equality of distributions in the baseline variables between recipients and non-recipients; the test is conducted for the restricted sample around the cut-off (1) and for the full sample of all respondents (2), broken down by batches and pooled across all three years. p-values of the tests reported. Samples drawn from the same distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Perceived returns - Alternative measure of dispersion I

Dependent variable: $[Pr(y_{max}\|HE) - Pr(y_{min}\|HE)] - [Pr(y_{max}\|SSC) - Pr(y_{min}\|SSC)]$						
Panel A - Uttarakhand	(1)	(2)	(3)	(4)	(5)	(6)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	29.217	29.198	29.198	29.198	29.198	29.198
$fellow$	5.961***	5.792***	10.388***	10.253***	10.255***	11.544***
	(1.30)	(1.23)	(3.34)	(3.33)	(3.32)	(3.66)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.04	0.09	0.10	0.10	0.10	0.10
Panel B - Orissa	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	51.403	51.403	51.403	51.403	51.403	51.403
$fellow$	-3.005	-4.114	-1.371	4.753	4.214	2.976
	(2.94)	(2.99)	(4.89)	(6.47)	(6.53)	(6.80)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R^2	0.00	0.166	0.170	0.176	0.178	0.180

Notes: Impact of the fellowship award on the dispersion of perceived returns to education, using the range between the probability of earnings falling in the highest income band and the probability of earnings falling in the lowest income band for higher education, higher secondary and lower secondary education. Percentage points (100 is 100%). The treatment variable is $fellows$, instrumented by $cutoff$ (Fuzzy RD). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Perceived returns - Alternative measure of dispersion II

Dependent variable: Signal to Noise Ratio $E[y\|HE]/SD[y\|HE] - E[y\|SSC]/SD[y\|SSC]$						
Panel A - Uttarakhand	(1)	(2)	(3)	(4)	(5)	(6)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	0.080	0.080	0.080	0.080	0.080	0.080
$fellow$	0.039***	0.039***	0.063***	0.062***	0.063***	0.069***
	(0.006)	(0.006)	(0.01)	(0.01)	(0.01)	(0.01)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.09	0.12	0.13	0.13	0.13	0.13
Panel B - Orissa	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	1.089	1.089	1.089	1.089	1.089	1.089
$fellow$	0.043	-0.076	-0.020	0.258	0.251	0.210
	(0.10)	(0.10)	(0.16)	(0.21)	(0.22)	(0.23)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	530	530	530	530	530	530
R^2	0.002	0.187	0.203	0.203	0.203	0.205

Notes: Impact of the fellowship award on the variance of perceived returns to education, using signal-to-noise ratio (mean over standard deviation of perceived returns). Robust standard errors in parentheses, clustered at the school-level. Percentage points (100 is 100%). Depending on the specification, the treatment variable is either $cutoff$ (OLS, and Cut-off) or $fellows$, instrumented by $cutoff$ (IV). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Perceived returns (mean), monotone only

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$ - **Monotone only**						
Panel A - Uttarakhand	(1)	(2)	(3)	(4)	(5)	(6)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	3.357	3.357	3.357	3.357	3.357	3.357
$fellow$	0.631***	0.574***	1.080***	1.031***	0.960*	1.059***
	(0.21)	(0.19)	(0.49)	(0.49)	(0.50)	(0.53)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.03	0.08	0.09	0.09	0.09	0.09
Panel B - Orissa	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	5.368	5.368	5.368	5.368	5.368	5.368
$fellow$	0.468	0.267	0.243	1.059	1.097	0.910
	(0.37)	(0.37)	(0.57)	(0.69)	(0.71)	(0.74)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	486	486	486
R^2	0.01	0.20	0.20	0.22	0.22	0.22

Notes: Excluding respondents who failed to recognize the principle of monotonicity when tested on basic probabilities. The direct impact of the fellowship award on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Perveived returns (SD), monotone only

Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$ - **Monotone only**						
Panel A - Uttarakhand	(1)	(2)	(3)	(4)	(5)	(6)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
fellow	-0.777***	-0.763***	-0.967***	-0.970***	-0.988***	-1.009***
	(0.10)	(0.09)	(0.28)	(0.28)	(0.30)	(0.32)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.13	0.18	0.18	0.18	0.18	0.18
Panel B - Orissa	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	1.808	1.808	1.808	1.808	1.808	1.808
fellow	-0.135	-0.048	-0.159	-0.259	-0.233	-0.200
	(0.16)	(0.20)	(0.32)	(0.43)	(0.44)	(0.46)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	486	486	486
R^2	0.002	0.21	0.21	0.21	0.21	0.21

Notes: Excluding respondents who failed to recognize the principle of monotonicity when tested on basic probabilities. The direct impact of the fellowship award on the standard deviation of expected wage, as measured by the difference between $SD_i[y|HE]$ and $SD_i[y|SSC]$ in 1,000 Rs ($16). The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Alternative construction of perceived returns

Dependent variable: $E_i[y|HE] - E_i[y|SSC]$ - **Alternative construction**						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Uttarakhand	Fuzzy Regression Discontinuity (IV)					
	Lower		Upper		Middle	
Mean of dep. Variable	3.424	3.422	3.425	3.423	3.425	3.422
$fellow$	0.673***	1.369***	0.673***	1.379***	0.673***	1.374***
	(0.17)	(0.49)	(0.17)	(0.49)	(0.17)	(0.49)
Forcing	No	Quartic	No	Quartic	No	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	514	512	512	512
R^2	0.04	0.10	0.04	0.10	0.04	0.10
Panel B - Orissa	Fuzzy Regression Discontinuity (IV)					
	Lower		Upper		Middle	
Mean of dep. Variable	5.372	5.372	5.371	5.371	5.370	5.370
$fellow$	0.735**	1.690**	0.737**	1.698**	0.739**	1.706**
	(0.36)	(0.80)	(0.36)	(0.49)	(0.36)	(0.81)
Forcing	No	Quartic	No	Quartic	No	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R^2	0.022	0.198	0.022	0.198	0.022	0.198

Notes: Alternative construction of perceived returns to education based on the lower, middle and upper bin of each income category (using $25,000$ Rs for the last bin in which $> 20,000$ Rs). The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Perceived returns (Mean), excluding batch 3 (Uttarakhand)

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$ - **Batch 1 & 2 only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	3.379	3.375	3.375	3.375	3.375	3.375
$cutoff$	0.543***	0.531***	0.990***	0.990***	1.008***	1.006***
	(0.15)	(0.16)	(0.28)	(0.28)	(0.31)	(0.32)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.02	0.05	0.06	0.06	0.06	0.06
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	3.379	3.375	3.375	3.375	3.375	3.375
$fellow$	0.606***	0.591***	1.332***	1.327***	1.463*	1.506***
	(0.17)	(0.18)	(0.44)	(0.43)	(0.50)	(0.55)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	367	367	367	367	367
R^2	0.03	0.06	0.08	0.08	0.08	0.07

Notes: Robustness of our main results to the exclusion of batch 3, for which we reject the McCrary test of the absence of endogenous sorting around the cut-off. We measure the direct impact of the fellowship award on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that is 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Perceived returns (SD), excluding batch 3 (Uttarakhand)

Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$ - **Batch 1 & 2 only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	-0.084	-0.083	-0.083	-0.083	-0.083	-0.083
$cutoff$	-0.657***	-0.665***	-0.722***	-0.731***	-0.690***	-0.678***
	(0.07)	(0.07)	(0.21)	(0.20)	(0.20)	(0.22)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.10	0.13	0.13	0.14	0.14	0.14
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.084	-0.083	-0.083	-0.083	-0.083	-0.083
$fellow$	-0.734***	-0.740***	-0.972***	-0.979***	-1.002***	-1.016***
	(0.07)	(0.07)	(0.21)	(0.20)	(0.23)	(0.26)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.13	0.16	0.16	0.17	0.16	0.16

Notes: Excluding batch 3 given the evidence of manipulation around the cut-off. The direct impact of the fellowship award on the standard deviation of expected wage, as measured by the difference between $SD[HE]$ and $SD[SSC]$ in 1,000 Rs ($16). Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that is 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. The unit of observation is the student. Robust standard errors in parentheses, clustered at the school-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Returns to education using point estimate (Orissa)

	Dependent variable: $E_i[y \mid HE] - E_i[y \mid SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect	Own returns			Others		
	Distribution	Point estimate		Distribution	Point estimate	
	Overall	Overall	Girls	Overall	Overall	Girls
Mean dep. var.	5.372	7.395	6.854	5.375	7.197	6.703
$fellow$	1.690***	3.391***	2.491*	1.829***	2.076*	2.716***
	(0.61)	(1.15)	(0.87)	(0.65)	(1.02)	(0.42)
Observations	550	550	265	550	550	265
R^2	0.198	0.207	0.322	0.216	0.208	0.326
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
On networks	Distribution	Point estimate		Distribution	Point estimate	
	Overall	Overall	Girls	Overall	Overall	Girls
Mean dep. var.	5.280	5.655	5.909	5.275	5.563	5.755
$fellow$	0.180	-1.006***	-0.247	-0.279	-0.496	0.197
	(0.00)	(0.37)	(0.68)	(0.38)	(0.62)	(1.14)
Observations	887	887	416	887	887	416
R^2	0.203	0.152	0.249	0.186	0.169	0.210
Panel C	(13)	(14)	(15)	(16)	(17)	(18)
On parents	Own returns			Others		
	Distribution	Point estimate		Distribution	Point estimate	
	Overall	Overall	Girls	Overall	Overall	Girls
Mean dep. var.	4.881	5.954	5.917	5.128	5.673	5.841
$fellow$	1.162***	2.496**	1.541	1.951***	2.745*	1.467
	(0.26)	(1.15)	(1.02)	(0.64)	(1.47)	(1.58)
Observations	423	443	217	443	443	217
R^2	0.327	0.304	0.324	0.301	0.212	0.288

Notes: Replicating main results of increased expected gain to completing HE vis-a-vis SSC using point estimates instead of the expected value derived from the elicited probability distribution. All results are estimated using Fuzzy RD with full set of controls and flexible forcing variable. Panel A shows the results for the direct effect on fellowship recipients and non-recipients. Panel B shows the indirect impact on those in their networks. Panel C shows the effect on parents of recipients and non-recipients. As a comparison, Columns (1), (7) and (13) report the estimates based on the measure of expected gain derived from the elicited distribution. Robust standard errors in parentheses, clustered at the cohort-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A11: Construction of the forcing variable

The forcing variable was generated by the NGO to rank and select the fellowship recipients. The selection process is divided into three stages:

In the first stage, non-eligible students are rejected and eligible students are assigned marks based on the information provided in the application form. The form asks for information about academic performance (marks), family background (household size, composition, employment and income) and a teacher assessment. Higher scores are assigned to students with better marks and teacher assessment, larger families and lower income. The total score in the first stage ranges from 0 (lowest) to 100 (highest). 65% of the score is formula-based and 35% is based on discretion.

In the second stage, applicants are given a written test to measure their analytical and essay writing skills. The students are asked to write a personal statement about their ambitions and their reasons for applying to the fellowship. The total score in the second stage ranges from 0 (lowest) to 100 (highest). The graders, recruited from the NGO staff and volunteer teachers, assign marks for the use of language (spelling and grammar), the structure of the essay and the originality of the content.

In the final stage, prospective fellows are interviewed with their parents and a home visit is scheduled. The interview serves to verify the motivation of the applicant, and the purpose of the home visit is to check the information (e.g. about family background and income) given in the application. A score of up to 100 points is given for the interview, broken down by four dimensions: genuine motivation (10), desire to excel in life (30), family involvement (30) and social sensitivity and awareness (30). Another score of up to 50 points is given for the home visit where statements about the family background are verified based on observable proxies of income (e.g. quality of housing, number of rooms). The interviewers and field officers were recruited from the NGO and volunteer teachers.

The final index is the sum of the scores in all three stages, ranging between 0 to 350. The fellowship is then given to the highest scoring students, with a threshold that is exogenously determined by the financial resources available to the NGO. In our analysis, we normalize the score to lie between 0 (lowest) and 1 (highest).

Appendix A12: Measurement of perceived returns

To measure perceived returns to education, we elicit the subjective probability respondents assign to receiving an entry salary of 0-5,000 Rs., 5,001-10,000 Rs., 10,001-15,000 Rs., 15,001-20,000 Rs. and above 20,000 Rs. We use showcards to illustrate the breakdown in a table (see below). The exact phrasing of the question is:

"Once you graduate from school, how do you think the probability of obtaining the following monthly incomes would change depending on completion of SSC, HSC and higher education, for the first 5 years of your career?"

Income group per month	Probability with		
	SSC	HSC	Higher Education
Rs. 0-5,000			
Rs. 5,001-10,000			
Rs. 10,001-15,000			
Rs. 15,001-20,000			
Rs. 20,001 and higher			

Note: Columns must sum up to 100%

Appendix A13: Description and sampling of Orissa (validation) study

We confirm our main results by examining the impact of the fellowship program implemented in Sambalpur (Orissa). The fellowship is funded by the same donor and nearly identical to the main study area in Dehradun (Uttarakhand), with the added advantage that it includes both boys and girls. The table below summarizes the main differences between both study sites.

	Uttarakhand (Site I)	Orissa (Site II)
Monetary award	7,000 Rs. p.a.	12,000 Rs. p.a.
Regular workshops	Yes	No
Target group	Boys	Boys & girls
Income threshold	Below 96,000 Rs. p.a.	Below 75,000 Rs. p.a.
Marks threshold	Above 60% SSC	Above 70% SSC
Intake	Grade 10	Grade 10
Intake studied	2008-2010	2009-2012
Beneficiaries	370	400
District literacy rate (Census '11)	77%	67%

Sampling and data collection

We conducted three cross-sectional surveys. The main survey targeted a random sample of students drawn from a sample of all 1,595 students who applied to the fellowship program between 2009 and 2012. Anticipating challenges in tracking applicants from the earlier batches, we oversampled to ensure the resulting dataset is balanced. In order to implement the RDD, the sample was stratified according to students around the cut-off and in the remainder group. We sampled all 289 students around the cut-off and prioritized the cut-off sample during the data collection. The remaining 762 students were drawn from the remainder sample, yielding a planned total sample size of 1,051.

Since the implementing NGO did not keep updated records of the addresses of unsuccessful applicants, tracking down previous applicants was a major challenge during data collection. To alleviate concerns of systematic non-response and allow the application of the RDD, the main effort during data collection has been focused on obtaining a balanced cut-off sample: Out of the 289 students around the cut-off, 230 students were covered (79%), but logistical constraints limited a similar tracking exercise for the remainder sample, where only 333 students were covered (43%).

Given the low coverage of the remainder sample, the main concern is one of systematic non-response bias. Even though the average annual household income is statistically indistinguishable between the actual and planned sample, students in the realized sample have, on average, slightly higher grade 10 marks than the average students from the planned sample. Once limiting the balance checks to the cut-off sample, however, there is no evidence of a systematic non-response bias. Given the potential sampling bias, subsequent analysis was conducted both using the full sample and the cut-off sample only.

For each of the applicants covered, we conducted a second survey targeting their parents to capture potential indirect impacts of the fellowship. The survey aimed to capture attitudes of parents towards investments in education, as well as collect a wide range of information on their social-economic background, time use and networks. From the 563 applicants covered, survey data was collected from 453 parents. Non-responses from the remaining parents were commonly attributed to refusal due to time constraints, but conditional on the applicant response there is no evidence of a systematic non-response bias among the parents.

We also conducted a third survey targeting those in the social and family networks of applicants. Respondents to the main survey were asked to name, in descending order, three of their closest neighbors, friends and siblings who were in grades 7-9, thus still eligible to apply for the fellowship and still in the process of deciding whether to invest in higher secondary education. We then captured the frequency with which our respondents interacted with these networks, with a particular focus on the interactions leading to exchanges of information about schooling, jobs and career choices. The final peer sample (896) was restricted by the fact that applicants were often unable to name a close peer: it was only possible to survey 91 siblings as many applicants did not have a sibling in grades 7-9. This constraint, however, does not vary differentially across networks of recipients and non-recipients.