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

Sandra Sequeira†, Johannes Spinnewijn‡and Guo Xu§

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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 standard deviations (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. Peers of fellows are however more informed about fellowship opportunities and report a higher intention to apply for the fellowship, thus contributing to the persistence of the potential impact of the fellowship across different cohorts.

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†London School of Economics, Department of International Development and STICERD, Houghton Street London WC2A 2AE, United Kingdom. (e-mail: S.Sequeira@lse.ac.uk)

‡London School of Economics, Department of Economics and STICERD, Houghton Street, London WC2A 2AE, United Kingdom (e-mail: j.spinnewijn@lse.ac.uk)

§London School of Economics, Department of Economics and STICERD, Houghton Street, London WC2A 2AE, United Kingdom (e-mail: g.xu2@lse.ac.uk)

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 the value of 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 for schooling performance 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 identify 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. The final score is based on both written tests and interview performance, and is not observed by the applicants. We exploit a discontinuity in the probability of being awarded the fellowship around a cutoff score defined by the pre-determined budget of the fellowship program. We take advantage of this same cutoff 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. Since exposure is randomly assigned to a set of peers that pre-date the fellowship, it is unrelated to other factors that drive perceptions about the value of education. This enables us to overcome problems of reflection and correlated unobservables that constrain the identification of peer effects.

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 standard deviations (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 9.2% points more likely to know about sources of funding for secondary education (mean: 27%) and 12.8% 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 both the external validity and the generalizability

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

of our findings. The point estimates on 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).

In this second study, we extended our survey to explore some of the particular mechanisms underlying our main results. In theory, recognition for educational success can directly shape expectations about future earnings through different mechanisms. In uncertain environments, recognition for educational success can, among others, 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 that is consistent with the second mechanism. Fellowship recipients are more likely to encourage their peers to apply for the fellowship and they report higher perceived returns to education not only for themselves, but also for others in their cohort.

The second study confirms the selective transmission of information across networks. While perceptions about returns to education do not spill over to peers, we 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. Taken together, our results suggest that uptake of the fellowship program is more likely to occur if a peer or a sibling has been recognized for her schooling efforts. The mechanism appears to be driven by changes in parental beliefs about the value of education and the transmission of information to peers on how to apply to different fellowship opportunities. These spillover effects then have important implications for the persistence of the impact of the fellowship award program across cohorts.

Our results lend 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), that information leads students to update beliefs about returns to education (Jensen, 2010; Nguyen, 2008; Wiswall and Zafar, 2011; Zafar, 2011) and that perceptions of risk are important determinants of schooling choices (Kodde, 1986; Altonji, 1993; Padula and Pistaferri, 2001). It directly adds to this literature by examining the mechanisms through which perceived returns to education are formed in the first place. In particular, it tests the importance of recognizing schooling effort on beliefs about returns to education.[2] This link between recognition (or lack thereof) and expectations can reinforce potentially 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. Finally, it contributes to the literature on the importance of peer effects for take up of social programs (Duflo and Saez, 2003; Kremer and Miguel, 2007; Dahl et al., 2014).

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. We validate our main findings in a second study site in Section 6. Section 7 explores the potential mechanisms through which rewards for educational performance could affect perceived returns to education, section 8 discusses robustness checks and section 9 concludes.

[2] The closest paper to our approach is Jensen (2010), which suggests that residential segregation can affect exposure to information that then shapes perceived returns to education.

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 years of schooling 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 overall returns to education, captured by a general parameter θ, and the individual's earning capacity determined by his or her ability and other individual-specific characteristics, captured by an individual-specific parameter λ_i. Individuals form beliefs about both general and individual-specific characteristics, and how they affect the distribution of future earnings. While we cannot observe the primitives underlying an individual's belief formation, in order to determine his or her perceived return to additional schooling, it is sufficient to measure gains in perceived expected utility across different levels of schooling. Assuming that the expected utility of uncertain earnings can be well approximated with mean-variance preferences, the expected lifetime utility simplifies to[3]

$$U\left(s_i|\lambda_i,\theta\right) \cong \Sigma_{k>0}\beta^k \left\{E[y_{i,k}|s_i,\lambda_i,\theta] - \eta_i var[y_{i,k}|s_i,\lambda_i,\theta]\right\} - C\left(s_i\right). \tag{1}$$

The return to additional schooling thus depends on its impact on both the mean and the variance of future earnings. In particular, an individual's choice between two degrees involving s_H and s_L schooling years will depend on $E[y_{i,k}|s_H,\lambda_i,\theta] - E[y_{i,k}|s_L,\lambda_i,\theta]$ and $var[y_{i,k}|s_H,\lambda_i,\theta] - var[y_{i,k}|s_L,\lambda_i,\theta]$. The difference in mean and variance of future earnings related to different schooling choices are the two statistics we will focus on in our empirical analysis.[4]

In low-income rural environments, perceptions of returns to education are likely to be formed in contexts of great uncertainty and poor information. Students have limited exposure to higher levels of education since parents may not have earned an education themselves, and individuals who did tend to migrate to urban areas. Households 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.[5] 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).[6] This may result in

[3]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.

[4]Note that while equation (1) suggests that risk preferences (η_i) may play a role in determining expected lifetime utility, differences in risk preferences in our sample wash out in the regression discontinuity analysis.

[5]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.

[6]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

a vicious cycle in which inaccurate beliefs translate into insufficient investments in education, affecting future labor market outcomes and keeping perceived returns to education low. The result can pose a 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 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, captured by λ_i above. 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.[7] If ability and schooling investments are either com-

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.

[7]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.

plements or substitutes, this feedback effect could have a direct impact on future schooling investments.

Besides providing an individual-specific signal, the reward can also change a student's perception about the overall value of education. A student who sees her studying efforts rewarded may positively update her beliefs about the returns to further investments in education. Alternatively, the reward may encourage students to seek information about earnings associated with more education. Since students in the developing world often underestimate the returns to education (Attanasio and Kaufmann, 2009; Jensen, 2010), the reward could reduce this pessimistic bias for successful applicants. These are examples illustrating that the recognition for schooling success can not only affect the individual-specific returns, but also the general returns to education, captured by θ above.

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.[8]

Beliefs about the returns to schooling can be driven by exposure to others experiencing different levels of academic success. An important channel through which peers can matter is through their own beliefs about the returns to education. If academic success

[8] 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).

leads to more positive beliefs about the general value of education, this may spill over into their family and social networks. Successful peers may also increase overall exposure to information about education and how to pursue funding opportunities that can enable additional years of schooling. Similarly, exposure to unrecognized peers may lead to lower perceived returns to education if students learn that effort is not rewarded. In principle, the direction of peer effects resulting from exposure to the schooling outcomes of peers is 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 observe).

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 alter the cost-benefit calculus of the fellowship program itself. The cost-effectiveness of any program that intends to increase educational attainment is highly dependent on the distribution of direct and indirect treatment effects, including those that reach beyond the immediately targeted group.

The main focus of our empirical analysis is to identify the presence and estimate the magnitudes of both the direct and peer effects of rewarding school performance. In section 7 we return to our conceptual framework and provide some suggestive evidence that highlights the potential mechanisms that underlie our findings.

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 non-governmental organization (NGO). Our main results are obtained from the first fellowship program, where we collected data in 2011, after the distribution of the fellowship. 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.[9]

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 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

[9] Appendix B5 contains a detailed discussion of the major differences across both study sites.

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 underreport 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. We provide a detailed description of the selection process in Appendix B2.

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 to 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]

3.2 Data

We conducted three cross-sectional surveys in 2011. 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. At the time of the survey, all batches have completed grade 12 (HSC), with the majority enrolled in higher education. Appendix Figure B1 summarizes the timing the fieldwork.

[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. See Appendix B2 for more details about the program implementation.

[11]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.

To ensure enough observations for the analysis of peer effects, the sample was stratified according to students close to the cutoff and in the remainder group.[13] The 400 students closest to the cutoff were covered. The overall targeted sample size was of 570 students, while the realized sample has 525 students (92%).[14] The survey data was supplemented with administrative data, which included the contact details, socio-economic background and application outcome of each applicant. Table 1 provides the basic summary statistics for all respondents as well as for the sub-sample around the cut-off.[15] There are no statistically significant differences between fellowship recipients and non-recipients around the cut-off.

We conducted a second survey targeting those in the social and family networks of students who were close to the cutoff (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.[16] 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

[13]The cutoff 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 cutoff was used to define the restricted sample of applicants with scores close to the cutoff. The remaining observations comprise the rest of the sample.

[14]We do not find any evidence of systematic non-response bias, as evidenced by Table A2.

[15]More detailed summary statistics is reported in Table A1.

[16]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.

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 A3).

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 but also to derive other moments in the distribution of expected earnings associated with different levels of investments in schooling.[17]

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.

3.3 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 cutoff value.

[17]See Appendix B4 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).

This cutoff was decided by the NGO in charge of the program, based on available funding for each year. Neither the cutoff nor the final score are observed by the applicants, so the recognition through the fellowship award carries an important signal even for those close to the cutoff. 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 cutoff.[18] 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 cutoff 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 cutoff of assignment to treatment (Campbell, 1969). A concern could for example emerge due to selective sorting or manipulation of students' scores close to the cutoff. 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 cutoff, marked by a solid vertical line. The dashed lines to either side of it define the sample of comparable students around the cutoff. Figure 2 confirms that all functions are smooth, exhibiting no discontinuities around the cutoff.[19]

[Figure 2 here]

[18] 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.

[19] We also formally test for the absence of a discontinuity in a Seemingly Unrelated Regression (SUR) model and cannot reject that the treatment coefficient is jointly zero for all covariates (see Table A11 in the Online Appendix.)

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 cutoff point.[20] 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.

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. In particular, we elicited the subjective probabilities respondents assign to receiving earnings in each of 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 average probabilities of each future earnings bin is reported in the Online Appendix Table A16.

The expected income for a given schooling level s is calculated by weighting each

[20]Tables 1 and A4 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 cutoff. 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 cutoff.

income band (using the lower bound) with its perceived probability $p_i(y_j|s)$[21]:

$$E_i[y|s] = \Sigma_j p_i(y_j|s) \times y_j \tag{2}$$

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.[22] We observe a stark increase in perceived returns to completing higher education vis-a-vis lower secondary education at the cutoff 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:

$$E_i[y|HE] - E_i[y|SSC] = \alpha + \beta \times treatment_i + g(score_i - cutoff_i, \boldsymbol{\gamma}) + \boldsymbol{X}_i'\delta + \epsilon_i \tag{3}$$

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 which is centered around the cut-off. $\boldsymbol{X}_i$ is a vector capturing several control

[21] The results are robust to alternative definitions of expected income using the upper bound and the midpoint of the income bins (Table A10 of the online appendix).

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

variables such as the age, household size, caste dummies, schooling stream dummies[23] 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.

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, and includes the most flexible polynomial controls for the forcing variable.

[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. Students above the cut-off report an expected monthly wage increase from completing higher education compared to lower secondary education by 744 Rs. (Column 1).[24] The estimated magnitude increases once accounting for the misassignment around the cut-off using the fuzzy regression discontinuity design (Column 2), consistent with an attenuation bias stemming from the imperfect compliance and fuzziness in assignment to treatment.[25] The estimates are stable

[23]The caste dummies are for Other Backward Castes (OBC), Scheduled Caste (SC), Scheduled Tribe (ST) and Muslim castes. The schooling streams are Arts, Science and Commerce.

[24]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 (See Table A17).

[25]We can also statistically reject that the OLS and IV estimates are equal (See Appendix A15). The difference between the reduced form and the IV estimate is driven by the imperfect compliance as shown in the first-stage Appendix Table A7.

when allowing for higher order polynomials (Columns 3-5).[26]

The point estimate of the preferred specification (Column 4) 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.[27]

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.[28]

[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.

[26]Our results are also robust when using fractional polynomials and fitting linear/quadratic functions of the forcing variable at each side of the discontinuity. The specification that minimizes the Akaike Information Criterion is the linear specification.

[27]Note that these results are also consistent with a discouragement effect among unsuccessful applicants to the fellowship, which would magnify the pessimistic bias.

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

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. Comparing HE with SSC we find that fellows report accurate returns relative to non-recipients and others in their network.

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

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:

$$SD_i[y|s] = \sqrt{\Sigma_j p_i(y_j|s) \times (y_j - E_i[y|s])^2} \tag{4}$$

where $E_i[y|s]$ is the expected perceived wage derived in (2). 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 perceived variability of 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 1,164 Rs ($20, Column 5).[29] These results are consistent across both the sharp (Column 1) and fuzzy discontinuity designs (Column 2-5).

[Table 3 here]

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.[30] 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.

[29]This effect is driven primarily by an increase in the variance in expected earnings when completing lower secondary school rather than by a decrease in the variance when completing higher education. (See Table A18).

[30]See Tables A5 and Table A6 in the online appendix.

5 Rewarding Schooling Performance: Peer Effects

5.1 Perceived Returns to Education

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 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:

$$Y_i = \alpha + \beta \times treatment_i + \boldsymbol{X}_i'\delta + \epsilon_i \tag{5}$$

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 restricting the analysis 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, corresponding to the level of treatment.

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).[31] 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 and 5). 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]

5.2 Information about Financial Support for Schooling

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 5). In our context, factual information is defined as knowledge about the eligibility criteria and

[31] Note that the peer sample is larger than the original applicant pool as we collected information on more than one participant in each applicants' networks (friends, neighbors and relatives).

the application process for the fellowship[32] (Columns 1), as well as knowledge about funding opportunities other than the fellowship under study (Columns 2). We also examine peers' reported intention to apply to the fellowship (Columns 3).

Those in the networks of successful applicants scored 4% points higher in the knowledge index, reflecting an improved understanding of the fellowship criteria and application procedures (Column 1).[33] We also find that those in the networks of successful fellows are 9% points more likely to know about alternative sources of funding (Column 2). 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 13% points more likely to consider applying to the fellowship in the subsequent round (Column 3).

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 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. Note that this also suggests an important way in which peer effects can increase the take up and long-run impact of fellowship programs.

[32]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.

[33]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.

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.[34] 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.[35] 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 6 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 2), which is nearly identical to the 1,369 Rs ($22.8) estimated in the first study site (Column 1). While the point estimate for girls only is slightly higher in Orissa (2,173 Rs, $36.2, Column 3), the overall direction and magnitude of the effects appears to be similar across genders.

[34]See Appendix B1 for the timeline and Appendix B5 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. For instance, in this second fellowship, we observe four cohorts of students. The last two cohorts in our sample experienced changes in the cutoff for eligibility to the fellowship, driven mostly by the general quality of the applicant pool and the capacity for the NGO to administer the fellowship. Unfortunately, we lack statistical power to be able to estimate treatment effects for the different cutoffs.

[35]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.

For the standard deviation, we find an effect for girls that is similar in magnitude, but it is no longer significant (Column 6).[36] While the point estimate for boys is smaller, we cannot statistically reject that the estimated effects are equal across genders.

[Table 6 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 7).

[Table 7 here]

For the most part, these results lend support to the external validity of our findings.[37] 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 both increase their mean earnings and decrease the variance in their earnings. In this section we provide suggestive evidence on the mechanisms through which recognition

[36] 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.

[37] 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).

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.[38] Distinguishing between these two broad mechanisms is important, as it can determine both the efficiency of additional schooling investments and the potential for spill-over effects.[39]

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. In the second survey in Orissa, we elicited the distribution of

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

[39] The workshops through which the fellowship installments were distributed in Dehradun did not convey information about the wage structure in the marketplace. Given (endogenous) variation in the number of workshops attended by different fellows, we directly test for this possibility and find no statistically significant relationship between reported perceived returns and the number of workshops attended by fellows in Dehradun, when controlling for observable individual characteristics. Moreover, there were no such workshops associated with the fellowship in Orissa and yet our main results were nearly identical.

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 that of others.[40] 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 8 here]

Table 8 shows that fellows report not only substantially higher returns to education for themselves (Column 2), but also for others (Column 4). The magnitude of the estimates is similar. 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.[41]

Table 9 reveals that fellowship recipients encourage, on average, 84% more peers to apply to the fellowship relative to non-recipients (Column 2). Since those in the networks of fellows and non-recipients are comparable and determined *before* the award, the observed encouragement pattern is also suggestive of an increase in the general value of education.[42] 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 9 here]

[40] 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?"

[41] 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.

[42] Note that it is still possible that fellows consider friends and siblings to be of comparable ability, and are therefore more likely to encourage them to apply for the fellowship. These results would then be consistent with the fellowship allowing fellows to extract a signal of individual ability, for themselves and for their friends and siblings. Note however that our sample of peers also includes neighbors, who are less likely to be perceived as being of similar ability.

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 9 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 suggestive of 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, among others.

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 10]

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 10, Panel A, Column 1). 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 (Column 2). They do not however report lower perceived dispersion in expected returns (Columns 3-4).

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 B). Parents of recipients are more likely to agree that "all children should pursue the highest education possible" (Column 5-6). They are also more likely to agree that their younger children should follow the success of the older ones (Column 7) and that children, in general, should postpone marriage until they have completed schooling (Column 8).

8 Robustness Checks

There are 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 argue that measurement error due to social desirability bias is unlikely given that we did not elicit any direct measure of returns to education, but instead, captured the expected wage distributions conditional on different years of schooling. Moreover, the data collection was conducted by an independent NGO and was advertised as a general study of trends in education, without any direct link to the program providing the fellowship. 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 rather than the other way round.[43] A second type of concern is that there might have been manipulation in the scores assigned to candidates around the cut-off. In Figure A1 we 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). In Uttarakhand, we find evidence of potential manipulation in the third batch of applicants. When we exclude this batch from the analysis, our results become even stronger. (Tables A11. For Orissa, we find no evidence of manipulation around the cut-off.

[Figure A1 here]

A third concern with our analysis relates to the challenge of identifying the correct network of peers of fellowship applicants through self-reported network data (Conley and Udry, 2010; Bandiera and Rasul, 2006). 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. In Table A2, we directly test for reporting differences between fellows and non-fellows whose networks we were able to fully sample and find no evidence of sampling bias. Moreover, we restrict the survey to networks that pre-dated the fellowship program to avoid the problem of endogenous network formation in response to the treatment itself.

[43] For a more detailed discussion of measurement error in our outcome of interest see Section A of the Online Appendix.

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 through which perceived returns to education may be formed in the first place. 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. Recognition for performance increases the short-run financial benefits of schooling and may motivate students to seek out information on future financial rewards associated with further schooling investments. 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 the transmission of information on 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 spillover 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 the long-term payoffs associated with schooling effort.

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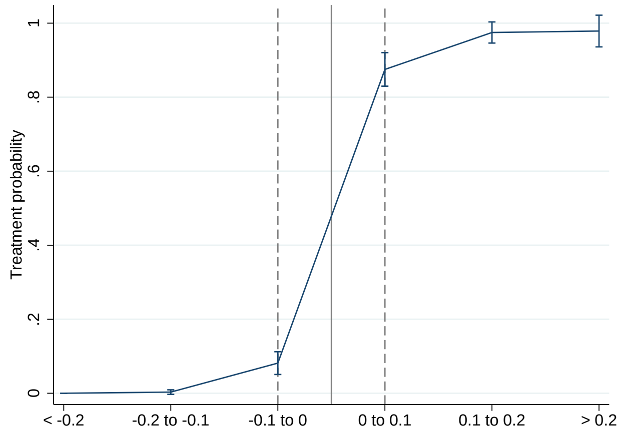
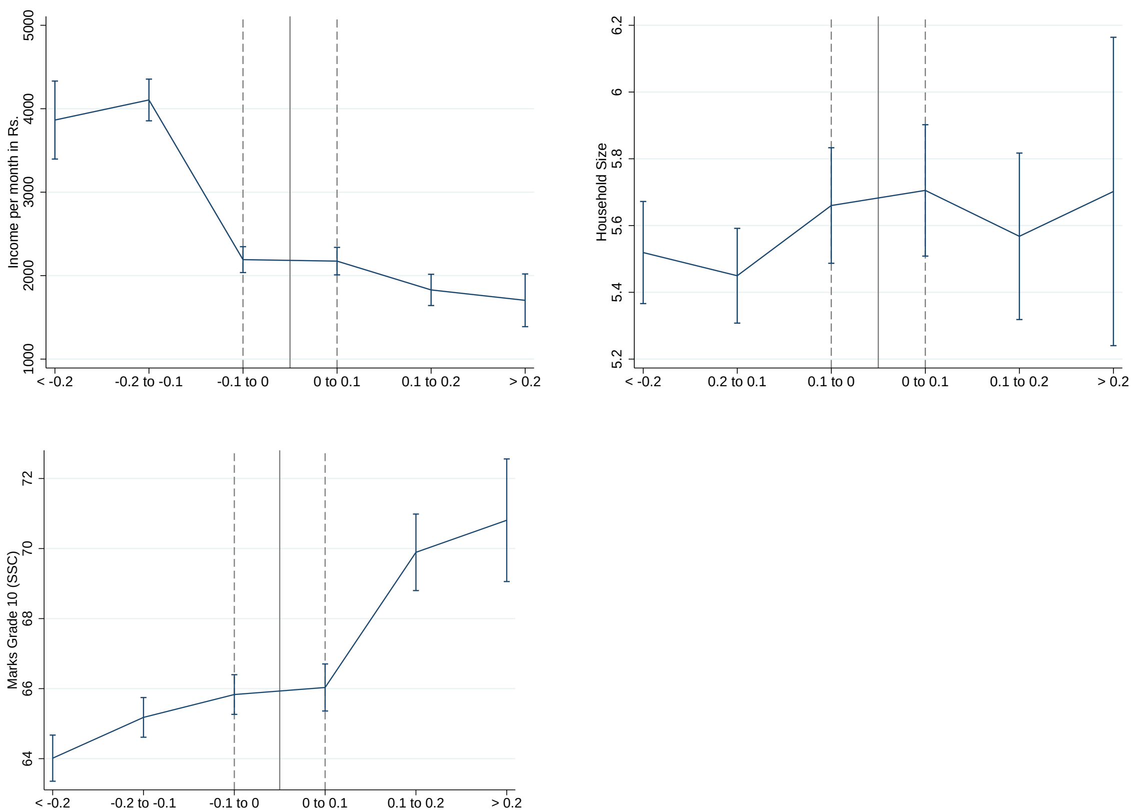
Figure 1: Probability of treatment as a function of the forcing variable



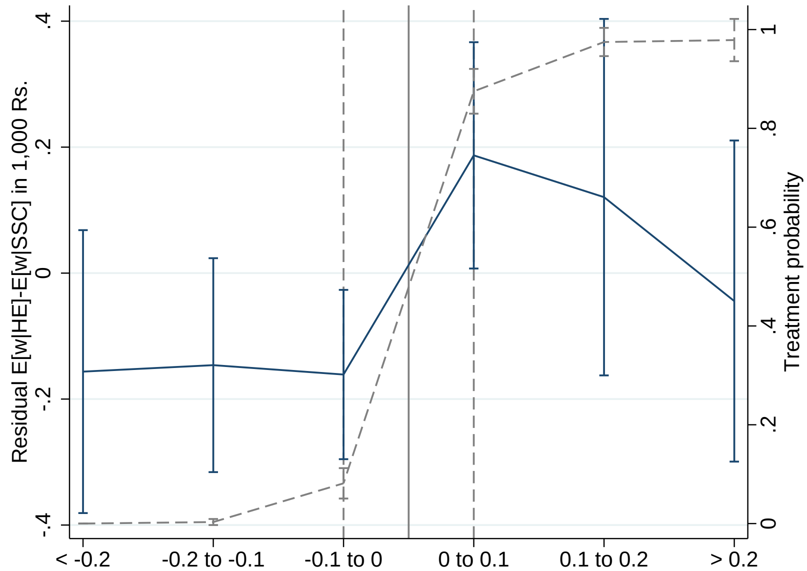
Notes: The forcing variable is normalized around the cut-off. Solid line indicates the cut-off, dashed lines indicate the sample "close" to the cut-off.

Figure 2: Baseline variables as a function of the forcing variable



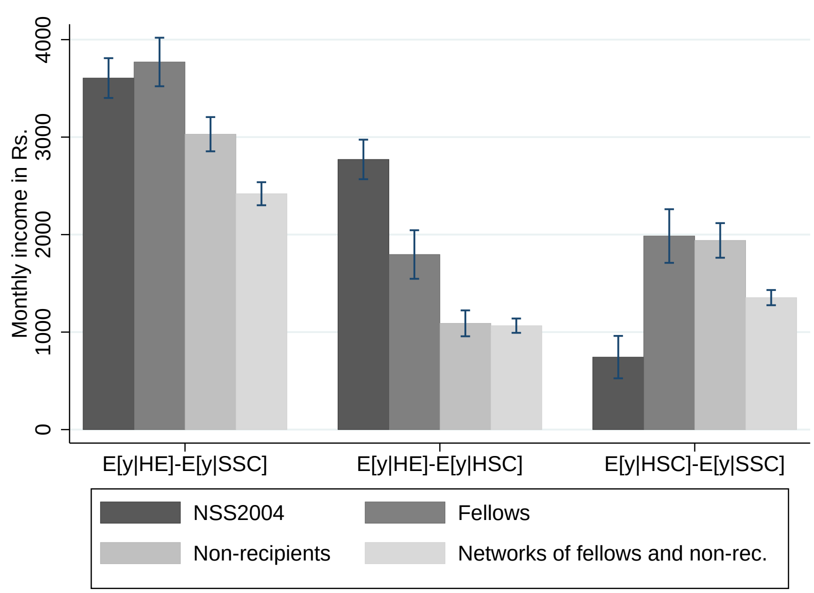
Notes: Solid line indicates the cut-off, dashed lines indicate the sample "close" to the cut-off.

Figure 3: Perceived returns to higher vs. lower secondary education



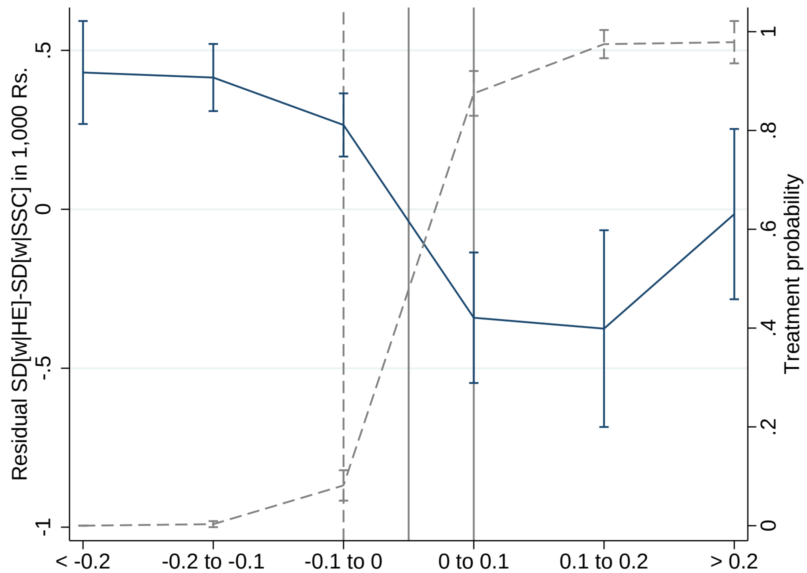
Notes: Residual differences (controlling for observables) between perceived average returns to higher (HE) and secondary education (SSC) as a function of the forcing variable. Dashed line shows the treatment probability.

Figure 4: Comparing perceived returns to actual (Mincerian) returns



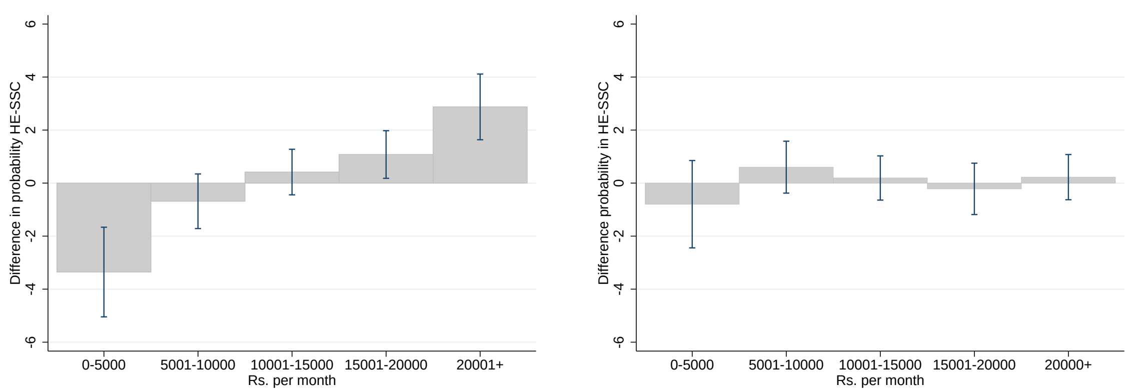
Notes: Comparing perceived returns to higher (HE) vs lower secondary education (SSC) with actual Mincerian returns from the Indian National Sample Survey 2004, adjusted for annual inflation between 2004-2008; broken down by perceived gains from higher secondary (HSC) vs lower secondary (SSC) as well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

Figure 5: Fellowship award and standard deviation of perceived returns



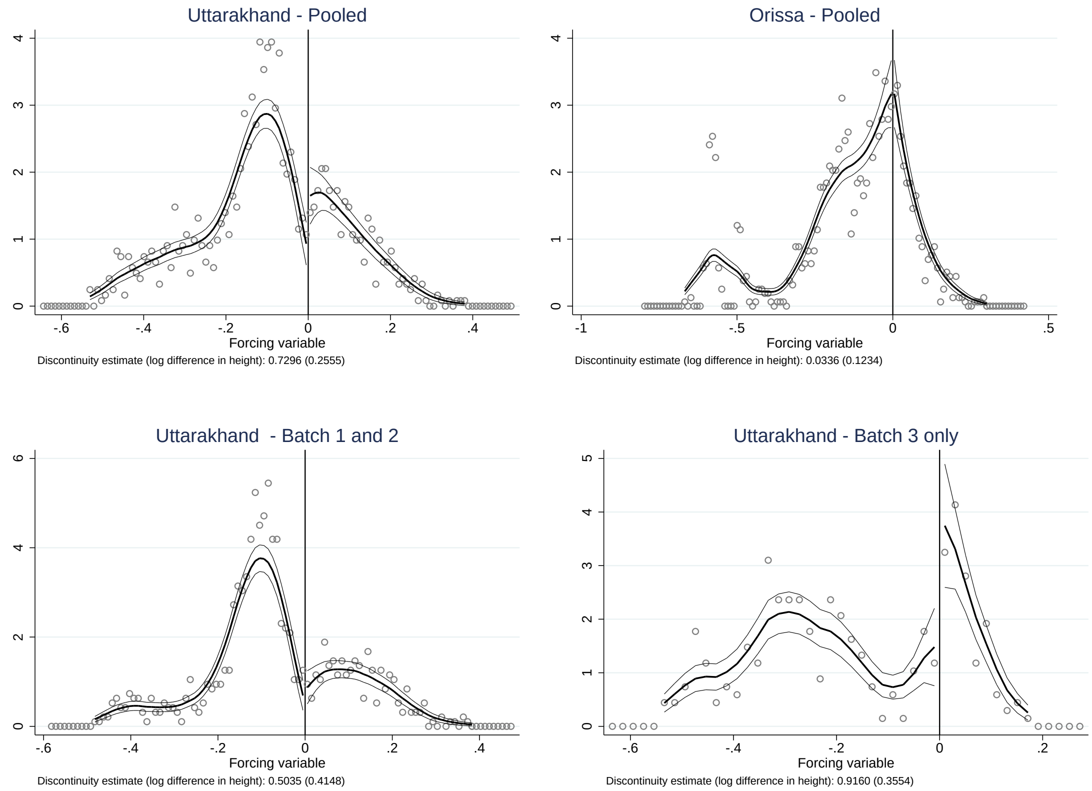
Notes: Residual differences (controlling for observables) between the standard deviation in perceived returns to higher (HE) and secondary (SSC) education as a function of the forcing variable. Dashed line shows the treatment probability.

Figure 6: Fellowship award and perceived probability of obtaining different entry salaries after graduation



Notes: 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 for manipulation around the cut-off



Notes: 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 (Uttarakhand)

Pooled	Full sample: Fellow	Full sample: Fellow - non-fellow	Full sample: N	Cut-off sample: Fellow	Cut-off sample: Fellow - non-fellow	Cut-off sample: N
Grade 10 marks	67.21	1.76***	523	65.53	-0.22	318
Income month (Rs.)	2214.2	-594.5***	497	2440.49	81.52	298
Household size	5.62	0.07	520	5.59	-0.01	316
Age at application	17.51	-0.15	523	16.395	-0.029	318
Caste: OBC	0.209	-0.01	522	0.220	0.042	318
Caste: ST	0.078	0.02	522	0.093	0.031	318
Caste: SC	0.145	0.03	522	0.174	0.037	318
Owns house	0.797	0.02	523	0.784	-0.037	318

Notes: Balance tests for fellows and non-recipients for the cut-off sample and the full sample. All three batches are pooled. Column *Fellow* shows the means for the fellows and the column *Difference* shows the difference in means between fellows and non-recipients. N is the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$				
	(1)	(2)	(3)	(4)	(5)
Mean dep. var.	3.424	3.424	3.424	3.424	3.424
cutoff	0.744***				
	(0.24)				
fellow		1.275***	1.258***	1.233***	1.369***
		(0.44)	(0.45)	(0.45)	(0.49)
Estimation	Sharp	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	-	27.34	27.27	26.17	28.10
Observations	512	512	512	512	512

Notes: The direct impact of the fellowship reward on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing higher education (HE) vis-a-vis secondary school (SSC). Column 1 shows the sharp regression discontinuity design estimate where *cutoff* is an indicator variable taking the value 1 if the student is above the cut-off and 0 otherwise. Column 2 reports the fuzzy regression discontinuity estimate, where the actual fellowship reward (*fellow*) is instrumented by *cutoff*. Columns 3-5 report the fuzzy estimates allowing for a flexible functional form for the forcing variable. The controls are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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: $SD_i[y\|HE] - SD_i[y\|SSC]$				
	(1)	(2)	(3)	(4)	(5)
Mean dep. var.	-0.169	-0.169	-0.169	-0.169	-0.169
cutoff	-0.631***				
	(0.17)				
fellow		-1.081***	-1.093***	-1.107***	-1.164***
		(0.23)	(0.24)	(0.25)	(0.28)
Estimation	Sharp	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	-	27.34	27.27	26.17	28.10
Observations	512	512	512	512	512

Notes: The direct impact of the fellowship reward on the standard deviation (SD) of perceived returns, as measured by the expected change in standard deviation in 1,000 Rs. ($16) from completing higher education (HE) vis-a-vis secondary school (SSC). Column 1 shows the sharp regression discontinuity design estimate where *cutoff* is an indicator variable taking the value 1 if the student is above the cut-off and 0 otherwise. Column 2 report the fuzzy regression discontinuity estimate, where actual fellowship reward (*fellow*) is instrumented by *cutoff*. Columns 3-5 report the fuzzy estimates allowing for a flexible functional form for the forcing variable. The controls are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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)

Panel A: Dep. var.	(1)	(2)	(3)	(4)
$E_i[y\|HE] - E_i[y\|SSC]$	Direct	Indirect (Networks)		
	Applicants	Pooled	Friends	Exogenous
Mean of dep. variable	3.501	2.419	2.417	2.422
fellow	0.942***	0.274	0.352	0.210
	(0.29)	(0.20)	(0.24)	(0.25)
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	No	No	No	No
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	97.81	268.7	281.8	219.9
Observations	312	575	262	313
Panel B: Dep. var.	(5)	(6)	(7)	(8)
$SD_i[y\|HE] - SD_i[y\|SSC]$	Direct	Indirect (Networks)		
	Applicants	Pooled	Friends	Exogenous
Mean of dep. variable	-0.250	1.090	1.117	1.067
fellow	-0.902***	0.235*	0.292*	0.182
	(0.17)	(0.13)	(0.16)	(0.15)
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	No	No	No	No
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	97.81	268.7	281.8	219.9
Observations	312	575	262	313

Notes: Peer effects of exposure to recipients vs. non-recipients on the perceived returns (mean and standard deviation (SD)) of those in the networks. For comparison, Column 1 and 5 report fuzzy estimates of the direct impact of the fellowship on recipients vs. non-recipients (Table 2 and Table 3) estimated around the cut-off. 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. Column 2-4 repeat the estimation for the indirect effect around the cut-off for all peers (Column 2), friends (Column 3) and siblings and neighbours (Column 4). Panel B: Pooled effects on the standard deviation (SD) of perceived returns of those in the networks of fellows around the cut-off, as measured by the expected change in standard deviation in 1,000 Rs. ($16) from completing higher education (HE) vis-a-vis secondary school (SSC). Column 6-8 repeat the estimation for the indirect effects on the standard deviation around the cut-off. Column 7 confines the sample to only friends and Column 8 restricts the sample to exogenously determined peers, which are siblings and neighbors. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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)

Dep. var.	(1)	(2)	(3)
Knowledge and	Indirect (Networks)		
intention to apply	Knowledge fellowship	Knows funding	Plans to apply
Mean of dep. variable	0.195	0.273	0.492
fellow	0.045*	0.092**	0.128**
	(0.02)	(0.05)	(0.06)
Specification	Fuzzy	Fuzzy	Fuzzy
Forcing variable	No	No	No
Controls	Yes	Yes	Yes
First stage F-statistic	268.8	268.7	268.7
Observations	575	575	575

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 (Column 1). Column (2) estimates the effect on whether the peer knows at least one alternative source of funding (other than the fellowship under study). Column (3) reports the effect on the intention to apply to the fellowship. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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: External validity - Direct results across both study sites

Panel A	(1)	(2)	(3)
Dependent var.	Uttarakhand	Orissa	
$E_i[y\|HE] - E_i[y\|SSC]$	Girls	Pooled	Girls
Mean dep. var.	3.424	5.373	5.216
fellow	1.369***	1.690**	2.173**
	(0.49)	(0.80)	(1.08)
Specification	Fuzzy	Fuzzy	Fuzzy
Forcing	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	28.10	58.58	34.75
Observations	512	550	265

Panel B	(4)	(5)	(6)
Dependent var.	Uttarakhand	Orissa	
$SD_i[y\|HE] - SD_i[y\|SSC]$	Girls	Pooled	Girls
Mean dep. var.	-0.169	1.796	1.853
fellow	-1.164***	-0.151	-0.690
	(0.28)	(0.47)	(0.60)
Specification	Fuzzy	Fuzzy	Fuzzy
Forcing	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	28.10	58.58	34.75
Observations	512	550	265

Notes: Comparing the effect of the fellowship on perceived returns to education (mean and standard deviation (SD)) across Uttarakhand and Orissa study sites. 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. *fellow* is a dummy variable that indicates whether the student is above or below the cut-off (sharp regression design) or the actual treatment instrumented by the cut-off (fuzzy regression design). All specifications use quartic polynomials to flexibly control for the forcing variable. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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 7: External validity - Peer effects on perceived returns of those in the networks

Panel A	(1)	(2)	(3)
Dep. var.	Uttarakhand	Orissa	
$E_i[y\|HE] - E_i[y\|SSC]$	Girls	Pooled	Girls
Mean of dep. variable	2.419	5.282	5.255
fellow	0.274	0.194	-0.247
	(0.20)	(0.67)	(0.69)
Specification	Fuzzy	Fuzzy	Fuzzy
Forcing variable	No	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	268.7	48.38	27.49
Observations	575	886	416
Panel B	(4)	(5)	(6)
Dep. var.	Uttarakhand	Orissa	
$SD_i[y\|HE] - SD_i[y\|SSC]$	Girls	Pooled	Girls
Mean of dep. variable	1.090	1.980	1.929
fellow	0.235*	0.014	0.095
	(0.13)	(0.31)	(0.42)
Specification	Fuzzy	Fuzzy	Fuzzy
Forcing variable	No	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	268.7	48.38	27.49
Observations	575	886	416

Notes: Comparing the peer effects on perceived returns to education (mean and standard deviation) 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. Panel B repeats the estimation using the expected change in the standard deviation in perceived returns. *fellow* is a dummy variable that indicates whether the student is above or below the cut-off (sharp regression design) or the actual treatment instrumented by the cut-off (fuzzy regression design). For Uttarakhand, the sample is confined to students around the cut-off. Orissa includes the full sample and uses quartic polynomials to flexibly control for the forcing variable. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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: Direct impact of fellowship reward on perceived returns for others (Orissa)

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$			
	(1)	(2)	(3)	(4)
	Own expected wage		Expected wage others	
Mean dep. var.	5.373	5.373	5.375	5.375
$fellow$	0.805	1.690**	1.036*	1.829**
	(0.59)	(0.80)	(0.57)	(0.81)
Forcing variable	Linear	Quartic	Linear	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	106.4	58.58	106.4	58.58
Observations	550	550	550	550

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. Showing the results using a fuzzy regression discontinuity design, where actual fellowship award (*fellow*) is instrumented by *cutoff*. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). 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 9: Direct impact of fellowship reward on encouragement and attitudes towards schooling/marriage (Orissa)

	Dependent variable: 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	26.06	26.06
$fellow$	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	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy	Fuzzy
First stage F-statistic	106.4	58.58	106.4	58.58	106.4	58.58
Observations	550	550	550	550	550	550

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)). Showing the results using a fuzzy regression discontinuity design, where actual fellowship award (*fellow*) is instrumented by *cutoff*. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). The unit of observation is the student. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Spill-overs on perceived returns (mean and SD) for parents (Orissa)

Panel A	(1)	(2)	(3)	(4)
Parental perceived returns	$E_i[y\|HE] - E_i[y\|SSC]$		$SD_i[y\|HE] - SD_i[y\|SSC]$	
	Own	Other	Own	Other
Mean of dep. variable	4.881	4.881	1.888	1.914
fellow	1.255***	2.026***	0.931**	0.826**
	(0.83)	(1.04)	(0.48)	(0.43)
Forcing variable	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy
First stage F-statistic	43.48	46.10	43.48	46.10
Observations	423	443	423	443
Panel B	(5)	(6)	(7)	(8)
Parental attitudes	Education for all		Role model	Delay marriage
Mean of dep. variable	0.734	0.734	0.645	0.586
fellow	0.184**	0.285**	0.150**	0.061
	(0.09)	(0.13)	(0.07)	(0.07)
Forcing variable	Linear	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes
Specification	Fuzzy	Fuzzy	Fuzzy	Fuzzy
First stage F-statistic	90.67	46.10	46.10	46.10
Observations	443	443	443	443

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 and standard deviation in 1,000 Rs (Panel A). Panel B: 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 (5), "If the oldest child is successful in school, the younger children should follow" (Column 7) and "My children should postpone marriage until they have completed their education" (Column 8). All specifications use a fuzzy regression discontinuity design, where the actual fellowship award is instrumented using the cut-off. The control variables are: age, household size and caste dummies (OBC, SC, ST) and stream dummies (Arts, Science and Commerce). The unit of observation is the student. Robust standard errors in parentheses, clustered at the school level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Online appendix: Robustness checks - Not for publication

Table A1: Summary statistics of baseline student characteristics

	Mean	SD	Percentile 25%	Percentile Median	Percentile 75 %	*N*
Grade 10 marks	66.404	5.546	62	65	70	523
Income per month (Rs.)	2478.64	1613.395	1500	2000	3000	497
Household size	5.588	1.451	5	5	6	520
Age at application	16.411	0.867	16	16	17	523
Caste: OBC	0.501	0.500	0	1	1	522
Caste: ST	0.068	0.253	0	0	0	522
Caste: SC	0.130	0.336	0	0	0	522
Owns house	0.787	0.409	1	1	1	523

Notes: Descriptive statistics (mean, standard deviation (SD) and percentiles) for baseline student characteristics. Castes are grouped into Other Backward Castes (OBC), Scheduled Tribes (ST), Scheduled Caste (SC).

Table A2: Baseline characteristics of planned and realized sample

Panel A: Pooled Uttarakhand	Planned sample (1)	Actual Sample (2)	Diff (1)-(2)
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 A3: Baseline characteristics of those in their networks (Uttarakhand)

		Full sample	
Pooled	Fellow	Fellow-Non fellow	N
Last year marks	61.446	0.099	523
Household size	5.94	0.17	575
Age	14.403	0.079	581
Caste: OBC	0.196	-0.036	581
Caste: ST	0.053	0.005	581
Caste: SC	0.149	-0.016	581
Owns house	0.79	-0.04	575

Notes: Balance test for those in the networks of fellows and non-recipients (applicants) for the cut-off sample. Column *Fellows* shows the means for the fellows and the column *Difference* shows the difference in means between fellows and non-recipients. N is the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Testing equality of distributions in baseline variables (p-values)

	Testing for equality of distributions	
Panel A: Pooled Uttarakhand	Cut-off (1)	Full sample (2)
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 A5: Perceived returns - Alternative measure of dispersion I

$[Pr(y_{max}\|HE) - Pr(y_{min}\|HE)] - [Pr(y_{max}\|SSC) - Pr(y_{min}\|SSC)]$				
Panel A: Uttarakhand	(1)	(2)	(3)	(4)
Mean of dep. var.	29.198	29.198	29.198	29.198
fellow	10.388***	10.253***	10.255***	11.544***
	(3.34)	(3.33)	(3.32)	(3.66)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	27.34	27.27	26.17	28.10
Observations	512	512	512	512
Panel B: Orissa	(5)	(6)	(7)	(8)
Mean of dep. var.	51.403	51.403	51.403	51.403
fellow	-1.371	4.753	4.214	2.976
	(4.89)	(6.47)	(6.53)	(6.80)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	106.38	78.60	64.89	58.58
Observations	550	550	550	550

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 A6: Perceived returns - Alternative measure of dispersion II

Signal to Noise Ratio $E[y\|HE]/SD[y\|HE] - E[y\|SSC]/SD[y\|SSC]$				
Panel A: Uttarakhand	(1)	(2)	(3)	(4)
Mean of dep. var.	0.080	0.080	0.080	0.080
fellow	0.063***	0.062***	0.063***	0.069***
	(0.01)	(0.01)	(0.01)	(0.01)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	27.34	27.27	26.17	28.10
Observations	512	512	512	512
Panel B: Orissa	(5)	(6)	(7)	(8)
Mean of dep. var.	1.089	1.089	1.089	1.089
fellow	-0.020	0.258	0.251	0.210
	(0.16)	(0.21)	(0.22)	(0.23)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	97.95	77.85	64.37	59.13
Observations	530	530	530	530

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 *fellow*, instrumented by *cutoff* (IV). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: First-stage: Fellowship award and cut-off (Uttarakhand)

	Dep. var. Fellowship award			
	(1)	(2)	(3)	(4)
Mean of dep. var.	0.535	0.535	0.535	0.535
Cutoff	0.583***	0.589***	0.573***	0.554***
	(0.11)	(0.11)	(0.11)	(0.10)
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	27.34	27.27	26.17	28.10
Observations	512	512	512	512

First-stage of the fuzzy regression discontinuity design (which instruments the actual fellowship award with the cutoff). Using the same specification as in the main specifications of the paper. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Perceived returns (mean), monotone only

	$E_i[y\|HE] - E_i[y\|SSC]$: Monotone only			
Panel A: Uttarakhand	(1)	(2)	(3)	(4)
Mean dep. var.	3.357	3.357	3.357	3.357
$fellow$	1.080***	1.031***	0.960*	1.059***
	(0.49)	(0.49)	(0.50)	(0.53)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	26.228	26.220	26.342	28.781
Observations	396	396	396	396
Panel B: Orissa	(7)	(8)	(9)	(10)
Mean dep. var.	5.368	5.368	5.368	5.368
$fellow$	0.243	1.059	1.097	0.910
	(0.57)	(0.69)	(0.71)	(0.74)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	87.89	65.68	54.65	50.10
Observations	486	486	486	486

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 A9: Perceived returns (SD), monotone only

	$SD_i[y\|HE] - SD_i[y\|SSC]$: Monotone only			
Panel A: Uttarakhand	(1)	(2)	(3)	(4)
Mean dep. var.	-0.148	-0.148	-0.148	-0.148
$fellow$	-0.967***	-0.970***	-0.988***	-1.009***
	(0.28)	(0.28)	(0.30)	(0.32)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	26.228	26.220	26.342	28.781
Observations	396	396	396	396
Panel B: Orissa	(7)	(8)	(9)	(10)
Mean dep. var.	1.808	1.808	1.808	1.808
$fellow$	-0.159	-0.259	-0.233	-0.200
	(0.32)	(0.43)	(0.44)	(0.46)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistics	87.89	65.68	54.65	50.10
Observations	486	486	486	486

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 A10: Alternative construction of perceived returns

$E_i[y\|HE] - E_i[y\|SSC]$ alternative construction			
Panel A: Uttarakhand	(1)	(2)	(3)
	Lower	Upper	Middle
Mean of dep. Variable	3.423	3.423	3.423
$fellow$	1.369***	1.379***	1.374***
	(0.49)	(0.49)	(0.49)
Estimation	Fuzzy	Fuzzy	Fuzzy
Forcing	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	28.10	28.10	28.10
Observations	512	512	512
Panel B: Orissa	Lower	Upper	Middle
Mean of dep. Variable	5.372	5.371	5.370
$fellow$	1.690**	1.698**	1.706**
	(0.80)	(0.49)	(0.81)
Estimation	Fuzzy	Fuzzy	Fuzzy
Forcing	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes
First stage F-statistic	58.58	58.58	58.58
Observations	550	550	550

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 A11: Perceived returns (Mean), excluding batch 3 (Uttarakhand)

	$E_i[y\|HE] - E_i[y\|SSC]$: Excluding batch 3			
	(1)	(2)	(3)	(4)
Mean dep. var.	3.379	3.375	3.375	3.375
$fellow$	1.332***	1.327***	1.463*	1.506***
	(0.44)	(0.43)	(0.50)	(0.55)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	48.18	51.80	31.79	32.52
Observations	367	367	367	367

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, $E_i[y|HE] - E_i[y|SSC]$. Showing the results using a fuzzy regression discontinuity design, where actual fellowship award (*fellow*) is instrumented by *cutoff* with varying flexibility of the forcing function. 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 A12: Perceived returns (SD), excluding batch 3 (Uttarakhand)

	$SD_i[y\|HE] - SD_i[y\|SSC]$: Excluding batch 3			
	(1)	(2)	(3)	(4)
Mean dep. var.	-0.083	-0.083	-0.083	-0.083
$fellow$	-0.972***	-0.979***	-1.002***	-1.016***
	(0.21)	(0.20)	(0.23)	(0.26)
Estimation	Fuzzy	Fuzzy	Fuzzy	Fuzzy
Forcing variable	Linear	Quadratic	Cubic	Quartic
Controls	Yes	Yes	Yes	Yes
First stage F-statistic	48.18	51.80	31.79	32.52
Observations	367	367	367	367

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). Showing the results using a fuzzy regression discontinuity design, where actual fellowship award (*fellow*) is instrumented by *cutoff* and allowing the forcing variable to take a flexible functional form. 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 A13: Returns to education using point estimate (Orissa)

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$					
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)
Forcing variable	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	58.58	58.58	34.76	58.58	58.58	34.76
Observations	550	550	265	550	550	265
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)
Forcing variable	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	48.37	48.37	27.49	48.37	48.37	27.49
Observations	887	887	416	887	887	416
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)
Forcing variable	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	43.48	46.10	16.33	46.10	46.10	16.33
Observations	423	443	217	443	443	217

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

Table A14: Testing smoothness of covariates around cut-off - Seemingly Unrelated Regression (SUR)

	Baseline covariates	
	(1)	(2)
	Cutoff	SE
Marks grade 10	-1.131	0.97
Age at application	-0.134	0.171
Income (Rs.)	367.52	302.09
Household Size	0.137	0.23
Other backward caste	0.030	0.082
Scheduled caste	0.078	0.068
Scheduled tribe	0.027	0.052
Owns house	0.015	0.079
Observations: 494		
Quartic polynomial, Sharp RDD		
Joint significance H_0: Cutoff= 0: p-value=0.484		

Notes: Testing for the presence of a discontinuity in baseline covariates, as proposed by Lee and Lemieux (2010). Column 1 reports the point estimate for the cut-off dummy. Column 2 reports the corresponding standard error. The p-value of the joint significance test for the cut-off dummy is reported at the bottom of the table. Robust standard errors clustered at the school-level. *** p<0.01, ** p<0.05, * p<0.1

Table A15: Testing equality of sharp vs. fuzzy estimates of perceived returns

	(1)	(2)	(3)
Outcome variable	Sharp	Fuzzy	Diff (1)-(2)
E[y|HE]-E[y|SSC]	759.54***	1,369.053***	-0.609**
	(0.26)	(0.49)	(0.30)
SD[y|HE]-SD[y|SSC]	-645.55***	-1.163***	0.518***
	(0.18)	(0.28)	(0.18)

Notes: Comparing the RDD estimates using sharp and fuzzy regression discontinuity design. Column 3 tests whether the difference between both estimates is statistically significant. Robust standard errors clustered at the school-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A16: Earning probabilities by education and award status

	(1)	(2)	(3)	(4)	(5)
Income bins (in 1,000 Rs.)	0 to 5	5 to 10	10 to 15	15 to 20	≥ 20
SSC (Grade 10)					
Non-recipients	44.705	25.743	16.415	9.402	3.830
	(0.64)	(0.32)	(0.27)	(0.31)	(0.40)
Recipients - Non-recipients	0.051	-0.693	-0.591	0.282	0.883
	(0.88)	(0.44)	(0.37)	(0.42)	(0.54)
Observations	520	520	520	520	520
HSC (Grade 12)					
Non-recipients	33.237	24.734	19.199	14.017	8.929
	(0.64)	(0.32)	(0.27)	(0.31)	(0.40)
Recipients - Non-recipients	-0.519	0.121	-0.844**	-0.158	1.357**
	(0.88)	(0.44)	(0.37)	(0.42)	(0.54)
Observations	517	517	517	517	517
HE (Grade 12+)					
Non-recipients	27.552	23.664	20.050	16.357	12.465
	(0.64)	(0.32)	(0.27)	(0.31)	(0.40)
Recipients - Non-recipients	-3.255***	-1.366***	-0.221	1.403***	3.721***
	(0.88)	(0.44)	(0.37)	(0.42)	(0.54)
Observations	516	516	516	516	516

Notes: Descriptive statistics of elicited subjective probabilities of receiving an entry salary in given income bin. Reporting mean for non-recipients and difference between recipients and non-recipients. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Breakdown of perceived returns (mean), level and difference

Dependent variable: Perceived returns (mean), level and difference						
	(1)	(2)	(3)	(4)	(5)	(6)
	HE-SSC	HE	SSC	HE-SSC	HE	SSC
Mean of dep. var	3.424	11.46	7.780	3.424	11.46	7.780
$cutoff$	0.760***	0.582**	-0.253			
	(0.26)	(0.27)	(0.16)			
$fellow$				1.369***	1.049**	-0.453
				(0.49)	(0.48)	(0.29)
Observations	512	512	516	512	512	516
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Forcing	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Specification	Sharp	Sharp	Sharp	Fuzzy	Fuzzy	Fuzzy
First stage F-stat	-	-	-	28.10	28.10	28.37

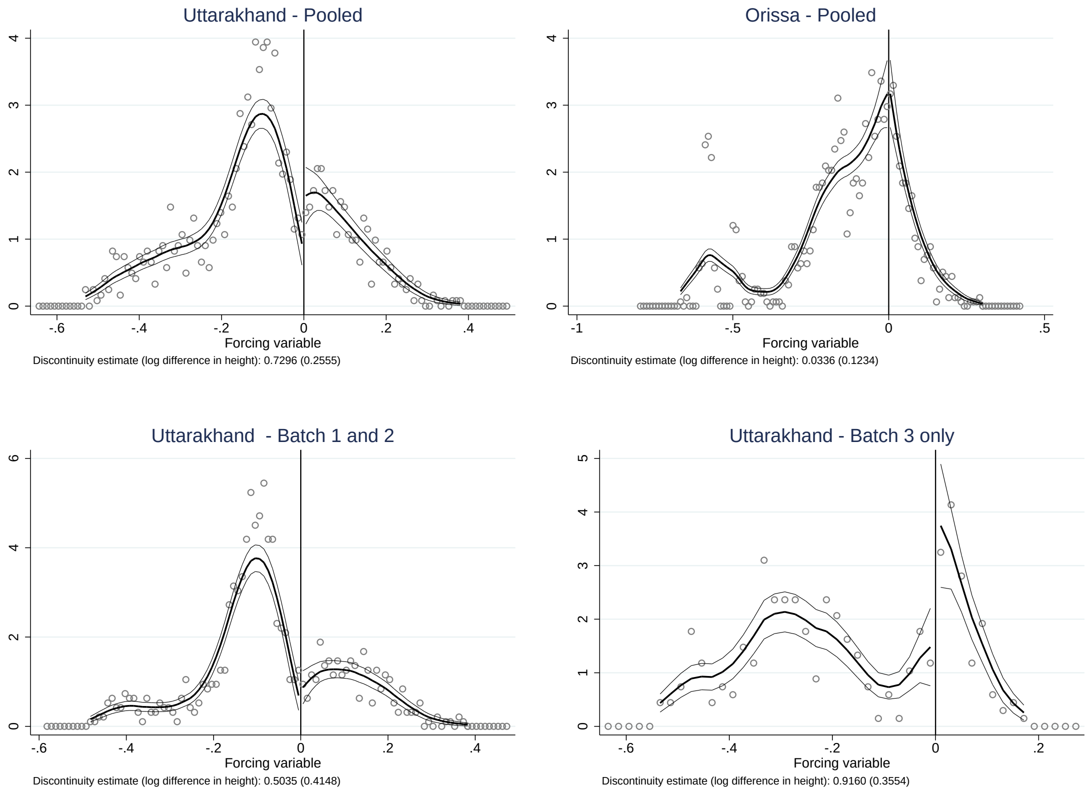
Notes: Robust standard errors clustered at the school-level. *** p<0.01, ** p<0.05, * p<0.1

Table A18: Breakdown of perceived returns (SD), level and difference

Dependent variable: Perceived returns (SD), level and difference						
	(1)	(2)	(3)	(4)	(5)	(6)
	HE-SSC	HE	SSC	HE-SSC	HE	SSC
Mean of dep. var	-0.169	6.661	6.830	-0.169	6.661	6.830
$cutoff$	-0.646***	-0.135	0.511***			
	(0.19)	(0.09)	(0.16)			
$fellow$				-1.164***	-0.243*	0.921***
				(0.28)	(0.14)	(0.26)
Observations	512	512	512	512	512	512
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Forcing	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Specification	Sharp	Sharp	Sharp	Fuzzy	Fuzzy	Fuzzy
First stage F-stat	-	-	-	28.10	28.10	28.10

Notes: Robust standard errors clustered at the school-level. *** p<0.01, ** p<0.05, * p<0.1

Figure A1: McCrary Test for manipulation around the cut-off



Notes: 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.

A Appendix A: Robustness Checks

A.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.[44] 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 rather than the other way round.

[44]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.

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 A8).[45] 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 A13).

A.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 **??** 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.[46] When examining each batch separately, we find that this effect is mainly driven by the third batch of students.

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

[46] 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.

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 A11. For Orissa, we find no evidence for manipulation around the cut-off.

[Figure A1 here]

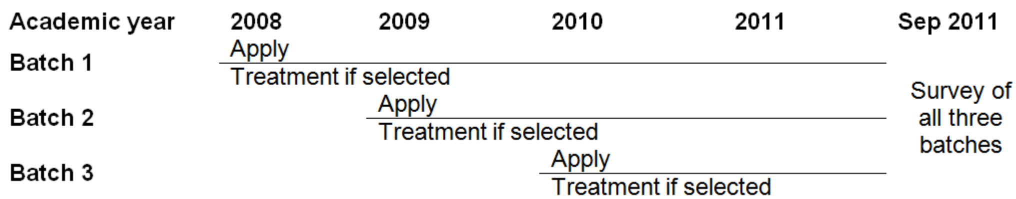
A.3 Identification of the Peer Network

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 A2, 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.

B Appendix B: Project Implementation

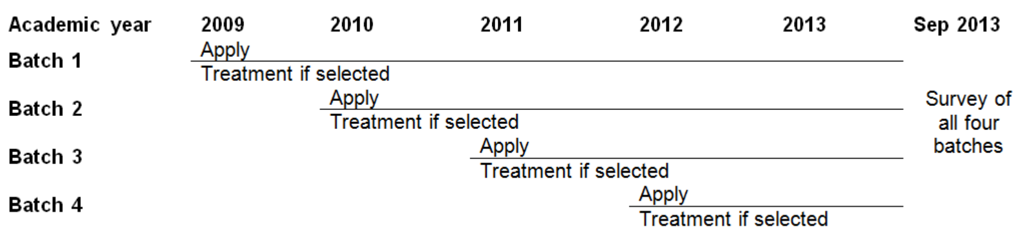
B.1 Timeline of main data collection

Study Site I - Dehradun, Uttarakhand



Notes: Timeline for Study Site I (Dehradun, Uttarakhand) of application, treatment, academic progression and data collection for the main survey in Dehradun district.

Study Site II - Sambalpur, Orissa



Notes: Timeline for Study Site II (Sambalpur, Orissa) of application, treatment, academic progression and data collection for the main survey in Dehradun district.

B.2 Fellowship Programs

We study two fellowship programs: The first runs in Dehradun district, Uttarakhand, and the second in Sambalpur district, Orissa. Both programs are funded by the same donor and hence follow comparable guidelines.

The aim of both programs is to enable talented secondary students from disadvantaged backgrounds to progress to higher education by providing a financial recognition (7,000 Rs. p.a. in Uttarakhand and 12,000 Rs.) and non-monetary assistance through the fellowship network. In Uttarakhand, additional workshops were provided to improve communication skills, spoken English, problem solving skills and stress management during examinations. The speakers were drawn from the NGO staff or volunteers. No explicit wage information was conveyed during these workshops. In Orissa, the non-monetary assistance was restricted to informal advising and support. The workshops were typically held in the offices of the NGO.

Both programs were advertised by sending out leaflets and posters to secondary schools across the district. While we are unable to determine the exact channel of information transmission (e.g. recommendation, or publicly visible posters), the interviews suggest that most of the first batch applicants have been informed by their teachers. For subsequent batches, information also spread by word of mouth. Given the wide targeting, the program was not concentrated in a few select schools. Overall, applicants came from 126 (96) schools in Uttarakhand (Orissa).

The fellowships were awarded in a public ceremony with representatives from the NGO and representatives of the local community. The payments were disbursed quarterly at the NGO. In Uttarakhand, the payments coincided with the quarterly workshops. Both programs are implemented by well-established local NGOs.

B.3 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 (about 30 students on average per intake) 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. Marks, household size and income are then normalized and equally weighted. 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).

B.4 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%

B.5 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	Girls	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%

B.6 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.