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

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Abstract

How are perceptions about the value of education formed? In this paper we test two specific mechanisms through which individuals may form expectations about returns to investments in education: receiving recognition for one's schooling performance, and exposure to successful students through family or social networks. To do so we study the impact of a fellowship program recognizing the schooling performance of young girls in secondary school in India. We find that being recognized for academic performance is associated with a significant increase in the perceived value of education, by both increasing the expected earnings and decreasing the perceived uncertainty associated with additional years of schooling. Being exposed to successful students does not affect perceived returns to education for those in their family or social networks. This exposure is however associated with holding more information on potential sources of funding for schooling and a higher intention to apply for the fellowship.

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1 Introduction

Investments in human capital have long been considered a fundamental part of any sustainable process of economic development and growth (Barro, 1998; Romer, 1989; Mincer, 1974). And yet, despite growing evidence of both the importance of education in the formation of human capital and of high individual returns to schooling (Kaufmann and Attanasio, 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 discounted benefits accrued by the household in terms of future income. In the developing world, perceptions of returns to education are however 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 (Levhari and Weiss, 1974; Dominitz and Manski, 1996; Jensen, 2010; Delavande et al., 2011). While a growing empirical literature has documented the importance of perceived returns to education in driving actual educational decisions (Padula and Pistaferri, 2001; Belzil and Hansen, 2002; Nguyen, 2008; Attanasio and Kaufmann, 2009; Jensen, 2010), the mechanisms through which perceived returns to education are actually formed in the first place remain poorly understood.

In this paper, we analyze the empirical relevance of two particular mechanisms. First, we examine how recognition 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), there is still limited empirical evidence on peer effects in the formation of perceptions about education.

To analyze the link between rewards for educational performance and perceptions we measure the impact of a fellowship program rewarding high performing girls in secondary school in India on perceptions of future wages associated with the completion of different levels of schooling. To investigate if the effect of rewards for academic performance is causal, we adopt a fuzzy regression discontinuity design. In our setting, the fellowship is awarded to girls pursuing secondary education in India based on a continuous score that measures each student's academic performance. We exploit a discontinuity in the probability of being awarded the fellowship around a cut-off score that depends on the pre-determined budget of the fellowship program. We then take advantage of this same cut-off to identify family and social networks that are exogenously exposed to successful students who either just made the pre-determined award criteria or came very close to meeting it.

We present three main findings. First, we show that perceived returns to education are highly sensitive to recognition for schooling performance. Educational rewards have a positive and statistically significant effect on the perceived returns to education of awardees: completing higher education relative to lower secondary school is perceived by fellowship recipients to increase the expected monthly entry salary by 1,369 Rs ($23[1] or 0.74 SD) in the first five years after graduation. Second, fellowship

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

recipients 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). Overall, those who are 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. Being recognized for schooling performance also leads to more accurate perceptions of returns to higher education, when measured against existing wages for entry-level jobs in the marketplace. Third, we find no evidence to support the hypothesis that being exposed to successful students recognized for their efforts affects perceived returns to education of those in their social or family networks. We do however find that peers in the network of successful students are 11.6% more likely to know about alternative sources of funding and 14.1% more likely to consider applying for the fellowship. We provide evidence of the robustness of our results and perform the standard tests to validate the identification assumptions underlying our regression discontinuity design.

Our approach represents an important departure from the literature, which has mostly focused on how educational inputs lead to educational outcomes. Understanding the reverse link of how educational performance affects perceived returns to education is particularly important as it holds potential to reinforce unequal investments in education, and consequently schooling outcomes, across time. Similarly, measuring peer effects is relevant not only because it highlights a mechanism through which expectations of returns to education can be formed, but also since they can potentially alter the cost-benefit calculus of the fellowship program itself. The cost-effectiveness of any program is highly dependent on the distribution of direct and indirect treatment effects, including those that reach beyond the targeted group. At a more general level, our paper contributes 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, our results also lend further support to studies showing that low-income groups in the developing world underestimate returns to education (Kaufmann and Attanasio, 2010; Kaufmann, 2008; Nguyen, 2008; Jensen, 2010) and that perceptions of risk in educational investments are important determinants of schooling choices (Padula and Pistaferri, 2001).

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

2 Conceptual Framework

2.1 Education as a Risky Investment

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). Demand for education may also be driven by perceptions of risk associated with investments in human capital. When determining schooling investments, individuals face ex ante drop out risk, wage risk (due to the shifting market value of education), and ability risk as they may mis-estimate where they will stand in the post-education earnings distribution. The theoretical and empirical literature on schooling choices under uncertainty is yet to converge on whether higher perceived risk increases (Belzil and Hansen, 2002) or decreases (Levhari and Weiss, 1974; Eaton and Rosen, 1980) investments in schooling.

Consider an individual i who chooses how much to invest in schooling, trading off the (opportunity) cost of schooling against its impact on her future income distribution. The optimal schooling investment s maximizes the individual's expected lifetime utility

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

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

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

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

[2]Note that this approximation is exact if earnings are normally distribution and the individual

In low-income rural environments, perceptions of the returns to education are likely to be formed in contexts of great uncertainty and poor information. Students will often have limited exposure to higher levels of education since parents may not have earned an education themselves, and individuals who did tend to migrate to urban areas. Households will also have limited access to information on earnings and unemployment rates for different schooling scenarios given that labor market data are seldom gathered and disseminated in any systematic way.[3] Households from low-income groups are likely to form erroneous beliefs about the returns to education, both the general and individual-specific component, which then shape their schooling decisions (Attanasio and Kaufmann, 2009; Jensen, 2010).[4] This may result in a vicious cycle in which inaccurate beliefs translate into insufficient investments in education, conditioning labor market outcomes and further reducing perceived returns to education. The end result can pose a great policy challenge of significant heterogeneity and inequality in schooling outcomes, even when, absent variations in the source and type of information available, preferences about schooling trade-offs are similar. In this context, understanding how perceptions about the mean and the variance of returns to education are formed in the first place becomes a central theoretical and empirical question.

In this paper we focus on two channels through which perceived returns to education can be formed. First, we investigate how recognition for one's educational success can

has CARA preferences with $\eta_i/2$ the parameter of absolute risk aversion.

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

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

directly shape expectations about future earnings associated with different levels of schooling attainment. Second, we examine the empirical relevance of peer effects as a channel through which expectations of returns to education can be formed, given that students 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

We begin by analyzing how perceived income distributions for different levels of education differ between successful and unsuccessful applicants to a fellowship which rewards students for their academic performance. In theory, this reward may directly affect perceived returns to education of fellowship recipients through various mechanisms.

For one, the reward may provide feedback to the students about their own ability and how their academic performance relates to the performance of others'. Students often have imperfect knowledge about their own skills and update their beliefs about their skills when receiving relevant feedback information: successful students are then expected to revise their beliefs upwards, while the unsuccessful students would revise their beliefs downwards.[5] If ability and schooling investments are complements, this feedback effect could have a direct impact on future schooling investments. The reward may also increase the actual returns to education for successful applicants. Becoming part of a network of fellowship recipients could potentially enhance income earning capabilities and employability upon completion of an educational degree. This networking dividend would again induce applicants to update their beliefs about their returns to education, which are then likely to affect future schooling investments.

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

Overall, while providing positive feedback in the form of a fellowship award may increase a student's motivation to continue studying, the effect on non-recipients, even when conditioning on ability, is likely to be negative (Compte and Postlewaite, 2004; Benabou and Tirole, 2002).

Besides individual-specific information, the reward can also provide more general information about returns to schooling effort. Given that students in the developing world will often underestimate returns to education (Attanasio and Kaufmann, 2009; Jensen, 2010), the reward could potentially convey important information about the value of exerting effort in education.

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 rewards for performance affect the perceived returns to education of individuals in the networks of fellowship recipients. 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). Consistent with these hypotheses, 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.

In theory, perceptions about returns to education are likely to spill over to the networks of fellowship applicants: interactions with others experiencing different levels of academic success and recognition, and consequently different realized returns to their own investments in education, can potentially drive beliefs about risks and rewards associated with additional years of schooling. The direction of peer effects resulting from exposure to the schooling outcomes of peers is however theoretically ambiguous, and is therefore ultimately an empirical question. Observing high-performing role models from those in your 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). Similarly, exposure to unrecognized peers may also either lead to lower perceived returns to education if students learn that effort is not rewarded or it may motivate students to exert more effort than their peers in order to achieve potential recognition. In the case of family networks, peer effects may be particularly detrimental if parents perceive an S-shaped curve of returns to education, in which the first few years of education pay much less in terms of future income than the following ones. These beliefs can then lead parents to concentrate their efforts and resources into educating fewer children, rather than investing across all siblings alike Banerjee and Duflo (2011). We directly test for differential peer effects by observing the impact of rewards on subjective expectations of returns to education of those in the family and social networks of award recipients and non-recipients.

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 a fellowship program that rewards high-performing female students attending secondary education in India. The fellowship program under study was launched by a non-governmental organization (NGO) in Dehradun district, province 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 for the quality of the documentation submitted in their application. Incomplete or poorly documented applications (e.g. lacking certified reports) were rejected. The second stage involved a written test, and the third stage consisted of an interview with the candidates and their parents. To ensure that potential candidates did not under-report their income to meet the eligibility criterion, random house visits were scheduled for about a quarter of the total applicants; 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, grade 10 marks and reported income levels. Successful applicants were then 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 fellowship would be withdrawn if students discontinued their studies or if the scholarship was spent for purposes other than education.[6]

3.2 Identification

In our setting, assignment to treatment was in principle determined by a student's score in the selection process relative to a cut-off value. The cut-off was decided by the NGO in charge of the program, based on available funding for each year. In practice, while we observe that assignment to treatment did not depend deterministically on the application score, figure 1 shows a strong discontinuity in the probability of assignment around the cut-off. We exploit this discontinuity as a source of variation to identify the causal relationship between the fellowship award and the outcomes of interest. To do so we use a fuzzy regression discontinuity design (FRD) in which we flexibily control for the student's score, and instrument the fellowship award for whether the student's score exceeds the cut-off value.(Lee and Lemieux, 2010; Thistlethwaite and Campbell, 1960; Hahn et al., 2001; Angrist and Lavy, 1999).

[Figure 1 here]

Identification further requires that all relevant factors besides treatment vary smoothly around the cut-off of assignment to treatment(Campbell, 1969). A concern could for example emerge due to selective sorting or manipulation of students' scores close to the cut-off. To directly test for the plausibility of this identifying assumption, Figure 2 plots important baseline characteristics of the applicants such as household size, household income levels and performance in 10th grade as a function of the forcing variable. The forcing variable is centered around the cut-off, marked by a solid verti-

[6]Cases where fellowships were withdrawn were extremely rare. In the three batches in our sample, only 8 fellowships were withdrawn due to lack of effort or for students entering the marriage market.

cal line. The dashed lines to either side of it define the sample of comparable students around the cut-off. Figure 2 confirms that all functions are smooth, exhibiting no discontinuities around the cut-off.

[Figure 2 here]

We apply the same intuition underlying the regression discontinuity design to estimate the spillover effect onto the social and family networks of fellowship recipients and non-recipients. We restrict our analysis to peers who are in the networks of students located close to the cut-off point. Since data limitations prevent us from applying a flexible control function approach to the peer sample, identification of peer effects requires that peers of award recipients and non-recipients in this subset close to the cut-off are similar. We indeed fail to reject tests for equality of variable means at conventional levels both when comparing the award recipients and non-recipients in this subset (see Tables 1) and when comparing their respective peers (see Table 2).[7] Table 3 also compares the distributions of observables for fellowship recipients and non-recipients. While some tests of equality of the distributions would be rejected when considering the full sample, no test is rejected for the applicants in the subsample close to the cut-off. This again suggests that targeted recipients and non-recipients and their peers are indeed comparable.

To mitigate concerns of endogenous network formation in response to the outcome of the fellowship process, we restrict our sample to networks that pre-dated the fellowship program. Besides friends, we also included siblings and neighbours in our analysis of spill-overs.

[7] More data on baseline characteristics is available for fellowship applicants than for their peers. For the peers, we account for household size and income (proxied by whether the household owns the house), which are unlikely to be affected by the treatment.

3.3 Data

We conducted three cross-sectional surveys. The main survey targeted a random sample of students drawn from a sampling frame of all students who applied to the fellowship program between 2008 and 2010. To ensure enough observations for the analysis of peer effects, the sample was stratified according to students close to the the cut-off and in the remainder group.[8] The 400 students closest to the cut-off were covered. The overall targeted sample size was of 570 students, while the realized sample has 525 students (92%). We do not find any evidence of systematic non-response bias, as evidenced by Table 4. Survey data was supplemented with administrative data, which included the contact details, socio-economic background and application outcome of each applicant.

We conducted a second survey targeting those in the social and family networks of students who were close to the cut-off (both for award recipients and non-recipients). Respondents to the main survey were asked to name, in descending order, three of their closest neighbors, friends and siblings who were female and in grades 8 or 9, thus still eligible to apply for the fellowship and in the process of deciding whether to invest in higher secondary education.[9] 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

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

[9] 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 are however similar when we exclude these cases from the analysis.

only possible to survey 57 siblings as many recipients and non-recipients did not have a sibling in grades 8 or 9. We find, however, no evidence that this constraint varies differentially across networks of recipients and non-recipients (Table 4).

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). Overall, 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.[10]

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 secondary 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 impact of rewarding schooling performance on the accuracy of perceived returns to education of fellows and non-fellows.

[10]Following common practice in the literature we resort to visual aids and examples to assist respondents with understanding probabilities prior to answering any questions on expectations (Dominitz and Manski, 1996; Attanasio and Kaufmann, 2009; Delavande et al., 2011; Luseno et al., 2003; Lybbert et al., 2004).

4 Rewarding Schooling Performance: Direct Effects

4.1 Expected Future Earnings

Our main measure of expected earnings is calculated based on the elicited individual distribution of income earnings for different levels of education. To measure the distribution for individual i, we divide income into the following bins $\mathcal{Y} = \{0 - 5,000; 5,001 - 10,000; 10,001 - 15,000; 15,001 - 20,000; > 20,000\}$. The choice of bin-width was based on the wage distribution of the Indian National Sampling Survey of 2004. The considered schooling levels are $\mathcal{S} = \{SSC; HSC; HE\}$, where SSC is equivalent to grade 10, HSC to grade 12 and HE to higher education degree programs.

The expected income is calculated by weighting each income band (using the lower bound) with its perceived probability $p_i(y_j|s)$[11]:

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

In Figure 4, we examine this direct effect of the fellowship award on perceived returns to education exploiting the regression discontinuity. Perceived returns to education are measured as the (standardized) additional gain from completing higher education (HE) vis-a-vis lower secondary school (SSC). After controlling for age, household size, caste, schooling stream[12] and cohort effects, we plot the residuals of this estimation against the forcing variable. We observe a stark increase in perceived returns to completing higher education vis-a-vis lower secondary education at the cut-off point. This increase coincides with the discontinuous jump in the probability of treatment,

[11] The results are robust to alternative definitions of expected income using the upper and middle bounds of the income bins (Table 18).

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

revealing that the fellowship award shifted perceived returns to higher levels of education.

[Figure 3 here]

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

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

where the left-hand-side $E_i[y|HE] - E_i[y|SSC]$ denotes the difference between average earnings when moving from a lower secondary school certificate (SSC) to a higher education degree (HE). The treatment variable represents a dummy variable indicating the fellowship award; $g(\cdot, \boldsymbol{\gamma})$ is a polynomial function with parameter vector $\boldsymbol{\gamma}$ that controls for the forcing variable and $\boldsymbol{X}_i$ is a vector capturing several control variables such as the age, household size, caste, schooling stream and batch dummies for each wave of the fellowship, for a total of three years of the program. The standard errors are clustered at the school-level to allow for arbitrary correlations of unobservables for 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, $cutoff_i$ (standard OLS in Panel A). This can be interpreted as our reduced-form estimate of the direct effect. Our preferred estimation, however, uses the fuzzy regression discontinuity design where the treatment variable ($fellow_i$) is instrumented with the dummy $cutoff_i$ (Panel B) to account for the mis-assignment to treatment around the cut-off.

[Table 5 here]

Table 5 confirms the previous graphical results: we detect a statistically significant impact of the fellowship award on average expected earnings. The reward for performance is associated with significantly higher average expected earnings. This result is robust to the inclusion of an extensive set of individual and family background controls (Panel A, Column 2), a flexible polynomial function to control for the forcing variable (Columns 3-6). Panel B repeats the same steps for the IV estimates. Using the fuzzy regression discontinuity, our estimation suggests that the fellowship increases perceived average gains in expected monthly earnings for obtaining a higher education degree vis-a-vis a secondary schooling degree by 1,369 Rs ($23) (Column 12). This corresponds to an increase in the perceived average gain of completing higher education of about 0.74 standard deviations. This sizable increase in the higher education premium corresponds to about 45% of the average monthly household income of fellowship applicants. The IV estimates are larger in magnitude than the OLS estimates, which is consistent with an attenuation bias stemming from imperfect compliance and fuzziness in assignment to treatment. We also find a similar estimate for the restricted sample of applicants around the cut-off in a regression that does not flexibly control for the students' score (Panel C). This result validates using the restricted sample and specification for the estimation of peer effects.

4.2 Variance of Expected Future Earnings

Based on the individual distributions elicited, we also construct the standard deviation of perceived future earnings for individual i for a given schooling level s:

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

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

[Figure 4 here]

Figure 4 suggests that the fellowship award decreased the variability of perceived future income associated with higher education. This is confirmed by the regression estimates presented in Table 6: 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 below the standard deviation of expected income associated with secondary education. The magnitude of this difference is also economically significant: the fellowship award decreases the difference in standard deviations by 1,163 Rs ($20). These results are consistent across both OLS (Panel A) and IV (Panel B) specifications. In Panel C we show that the results are again robust to restricting the analysis to the subset of students with scores close to the cut-off.

[Table 6 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, $p_i(y_{max}|s) - p_i(y_{min}|s)$ (Table 14) and the inverse of the coefficient of variation (signal-to-noise ratio), which enables a unit-free comparison across distributions of earnings for each schooling level (Table 15).

Overall, these results indicate robustly that fellows perceive investments in higher education to increase average earnings and to reduce earnings.

5 Rewarding Schooling Performance: Peer Effects

In this section we investigate whether changes in perceived returns to education triggered by rewards for academic performance spill-over into social and family networks. Figure 5 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 classes for recipients and non-recipients when finishing higher education (HE) relative to lower secondary education (SSC), 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 lowest income bands and a larger positive effect on the probability of ending up in the highest income bands. However, in contrast to the clear distributional shift to higher income bands of fellow's perceived returns to education (direct effect), we do not find a statistically significant differential effect on their peers (right). This already suggests that there are no detectable spillover effects in perceptions about the impact of education on expected earnings, but it could still have an impact on the variance in earnings.

[Figure 5 here]

5.1 Expected Value and Variance of Future Earnings

To test for peer effects in the mean values and variance of perceived returns to education, we estimate the following equation:

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

with Y_i equal to $E_i[y|HE] - E_i[y|SSC]$ and $SD_i[y|HE] - SD_i[y|SSC]$ respectively and the notation follows the specification in (2). We can no longer exploit the fuzzy RDD and flexibly control for the score variable as our sample is restricted to the peers of students with scores around the cut-off. Notice, however, that this restriction does not affect our estimates of the direct effects, which mitigates potential concerns about using this approach for estimating the peer effects (see Tables 5 and 6). Since several peers may be exposed to the same role model (fellow/non-recipient), the standard errors are clustered at the level of the role model.

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 7) and standard deviation (Table 8). Peer effects on perceived mean earnings are never statistically significant. For peer effects on perceived standard deviations, some estimates are marginally significant. In both cases, the estimated magnitudes are very small relative to the comparable estimates of the direct effects (see Panel in Tables 5 and 6). To directly test for treatment heterogeneity, we also break down the regressions by network type (sibling, neighbor and friend) but fail to detect any statistically significant differential spill-over effects across groups.

[Table 7 here]

5.2 Further Peer Effects

While we do not find peer effects on perceived returns to education, we find systematic evidence of the spilling-over of factual information from fellowship recipients to those in their networks (Table 9, 10, 11). In our context, factual information is defined as knowledge about the eligibility criteria and the application process for the fellowship[13] (Columns 1-2), as well as knowledge about alternative funding opportunities other than the fellowship under study (Columns 3-4) and reported intention to apply to the fellowship (Columns 5-6).

[Table 9, 10, 11 here]

Those in the networks of successful applicants were able to score 5% points higher in the knowledge index reflecting an improved understanding of the fellowship criteria and application procedures (Table 11, Column 4). 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. We also consider knowledge about alternative sources of funding and find that those in the networks of successful fellows are 11.6% points more likely to know such sources (Table 10, Column 4). Since knowledge about alternative sources is otherwise very low (with an average score of 27%), this represents a sizable improvement. Perhaps most importantly, these factual spill-overs seem to translate into investment decisions: those exposed to a successful fellow were 14.1% points more likely to consider applying to the fellowship in the subsequent round (Table 9, Columns 4).

[13] 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 four 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%, 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.

Our results suggest that while agents do not necessarily 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, a higher intention to apply for the fellowship and they were also better informed about alternative sources of funding that could enable them to continue their studies.

6 Discussion

While previous work has established the importance of perceived returns to education for educational investments and achievements, our results shed light on the reverse relationship. Students whose achievement in school is recognized perceive the value of education to be higher. Fellowship recipients expect education to increase their mean earnings more and to decrease the variance in their earnings less than non-recipients. The change in perceptions triggered by the reward, however, does not spillover to peers in the applicants' networks. One explanation for the absence of spillover effects is that the reward only reveals individual-specific information, by for example allowing the applicant to revise beliefs about her ability depending on her success, or by guaranteeing access to particular network dividends for successful applicants. In the next subsections, we present additional suggestive results that are difficult to square with this mechanism of individual-specific updating.

6.1 Accuracy of Perceived Returns to Education

We first analyze how perceived returns to education compare to actual average returns. 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 fellowship program is offered. We adjust for inflation using the annual inflation rates between 2004-2008[14].

[Figure 6 here]

Figure 6 compares the estimated coefficients of the difference between perceived and actual returns. 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 and the applicants' younger peers. The non-recipients seem to underestimate returns and this bias is even more pronounced for the applicants' peers who have not yet been given the opportunity to apply for the fellowship. 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 eliminate 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. This optimistic bias is smaller for peers, who still have to complete their secondary education.

Overall, these findings are consistent with previous evidence for pessimistic beliefs regarding returns to education: students' perceptions of expected earnings are significantly lower than the average earnings documented through our wage audit (Attanasio and Kaufmann, 2009; Jensen, 2010). However, receiving rewards for academic performance seems to close this gap significantly. If actual returns to education are not substantially higher for fellowship recipients than for non-recipients, this evidence suggests that the reward reduces pessimistic bias. which is consistent with

[14]World Development Indicators (2013)

some learning about the general returns to education taking place.

6.2 Own vs. Others' Returns to Education

If the reward for schooling performance allows fellows to extract a signal about their individual types, we would expect this to introduce a wedge between perceptions of own earning capabilities and those of others. To shed light on this, we compare the applicants' perceptions of own expected earnings and expected earnings of others in their cohort, conditional on completion of higher education.[15]

[Table 12 here]

Table 12 presents the results, which suggest that fellows report not only substantially higher levels for their own earnings, but also for others' earnings. With both sharp and fuzzy RD specifications we fail to detect a statistically significant difference between the expected increase in own earnings and the expected increase in others' earnings for recipients compared to non-recipients at the discontinuity point. The fact that fellowship recipients do not adjust expectations about future earnings for themselves alone but also for others does not support the hypothesis that rewarding schooling performance allows students exclusively to elicit their type or to reap a networking dividend. Instead, this provides (albeit only) suggestive evidence that the award may convey important information about the general value of education.

[15] While we elicited the full distribution of educational returns in the main sample of recipients and non-recipients for the respondents themselves, survey constraints prevented us from eliciting the full perceived distribution for others. Instead, respondents were asked to report average sectoral entry salaries for higher education graduates in their cohort. We construct a comparable point estimate for the mean by averaging across all sectors.

6.3 Encouragement to Continue Education

The impact of the reward of the fellowship on the encouragement of peers to join the fellowship program is likely to differ depending on which mechanism is at play. The reward would lead fellows to differentially encourage peers to apply to the program (or to seek alternative sources of funding) relative to non-fellows, if the main mechanisms at work were a learning effect or a networking dividend. If the reward signals the ability of the fellow, then fellows should be no more likely to encourage others to apply for the program. Table 13 reveals that fellows are indeed differentially more likely to encourage friends in their networks to apply for the fellowship award (Column 17). Fellowship recipients encourage, on average, 54% more peers to apply than non-recipients (Column 12). This complements the earlier results that peers of recipients express a stronger intention to apply to the fellowship (Table 9) and are also more likely to be aware of eligibility criteria and of alternative sources of funding (Table 10 and 11).

[Table 13 here]

While we are unable to firmly establish the mechanism through which rewards for schooling performance shape perceived returns to education, taken together, the evidence is consistent with the fellowship award sending a significant signal of the general value of education as a safe and high-return investment.

7 Robustness Checks

In this section we discuss two 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.

An important concern 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 respectively 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 exact correct answer. Our results, however, remain unchanged even when we remove from our analysis the respondents who did not 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 16 and Table 17).

We already checked whether potentially relevant factors besides treatment vary smoothly around the cut-off of assignment to treatment. In Figure 7 we also plot the number of observations in each bin against the mid points 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, which is suggestive of potential manipulation of the scores around the cut-off.[16] When examining each batch separately, we find that this effect is mainly driven by the third batch of students. For the first two batches, the evidence does not suggest sorting or manipulation of the forcing variable around the cut-off. Our main results become even stronger when we exclude the third batch, in which manipulation around the cut-off may have taken place (Table 19 and 20).

[Figure 7 here]

While a commonly used method in the literature, relying on self-reported network

[16] 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.

data (Conley and Udry, 2010; Bandiera and Rasul, 2006) raises some concerns. In our setting, the realized sample of peers (575) is 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 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 2, however, we directly test for differences between fellows and non-fellows whose networks we were able to fully sample. We find no evidence of sampling bias. A second concern is that networks may be endogenously generated in response to the outcome of the fellowship process. This would introduce the possibility of reverse causation when assessing the impact of exposure to a fellow on the perceptions of their networks. To mitigate this concern, we restricted the survey to networks that pre-dated the fellowship program. We also disaggregate our analysis to test the robustness of our results across endogenous (friends) and exogenous sources of networks (neighbors and siblings).

8 Conclusions

In this study, we document an important channel through which perceptions of returns to education can be formed. We find that receiving an award for schooling performance is strongly associated with higher (and more accurate) expectations of average earnings associated with higher levels of education, but also of less risky jobs and wage profiles relative to students with similar performance in school who failed to receive recognition for their efforts. While our design does not allow us to firmly establish the mechanism underlying this effect, we provide suggestive evidence that it is driven by an increased valuation of education and of the relationship between effort and reward, rather than by the extraction of a signal of each student's quality type or by any networking dividend associated with participation in the network of fellowship recipients. Fellowship recipients appear to perceive higher returns both for themselves and for others in their cohort upon completion of the same levels of schooling and they are more likely to encourage peers to seek funding to continue their studies.

We also explore a second channel through which perceived returns to education may be formed: exposure to role models. We investigate the impact of exposure to a fellowship awardee on perceptions of those in their family and social networks. While we find no robust evidence of peer effects on perceptions, peers of fellowship recipients are significantly more likely to identify the factual details of the application process, to be knowledgeable of alternative sources of funding and to express an intention to apply for the fellowship program in the future.

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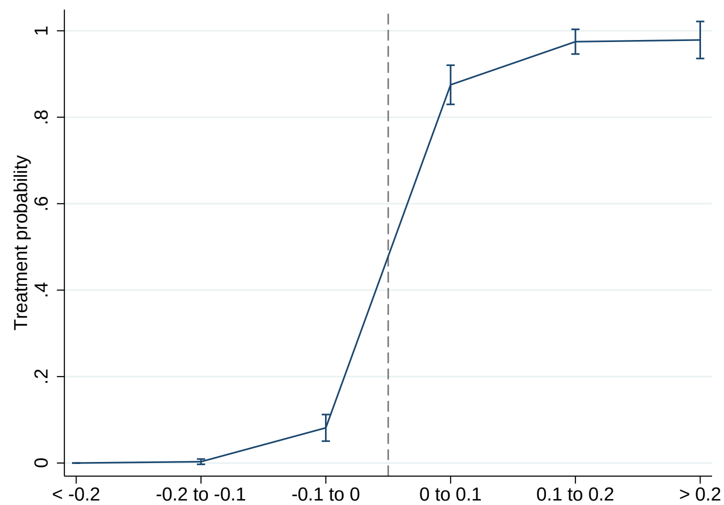

Figure 1: Probability of treatment as a function of the forcing variable, normalized around the cut-offs. Dashed line indicates the cut-off.

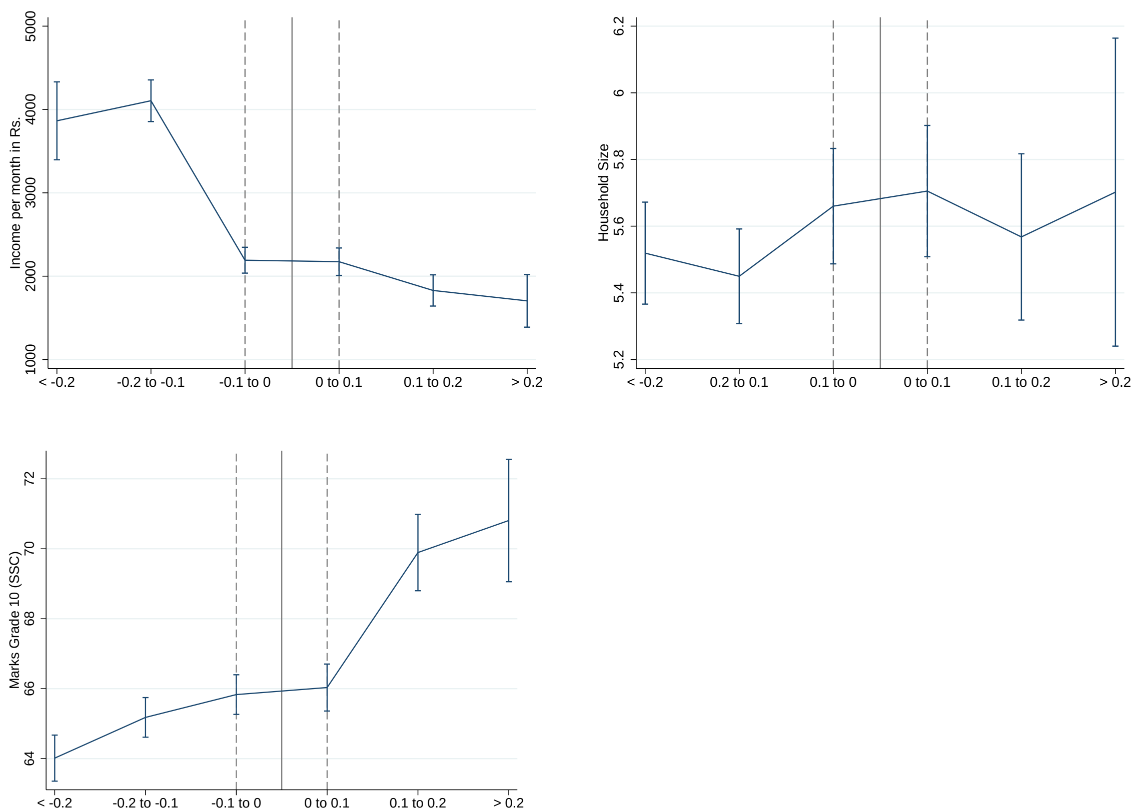

Figure 2: Baseline variables as a function of the forcing variable. Solid line indicates the cut-off, dashed lines indicate the sample "close" to the cut-off.

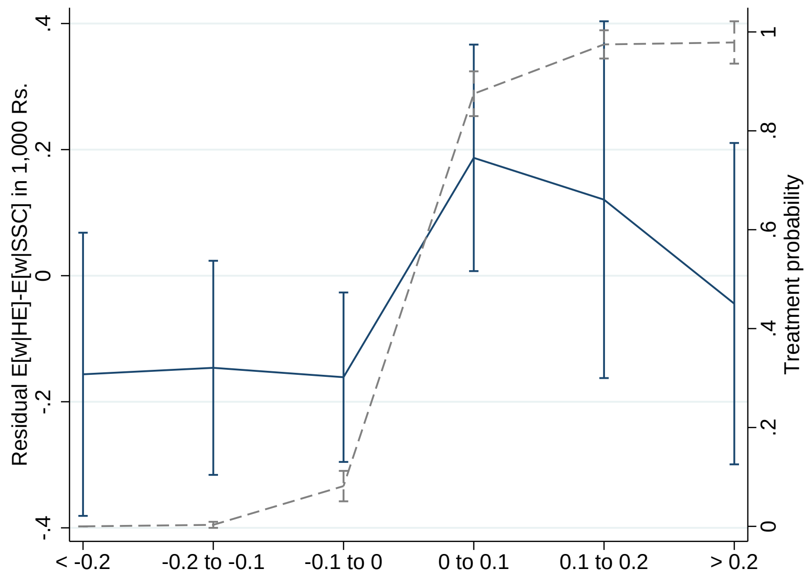

Figure 3: Residual differences (controlling for observables) between perceived average returns to higher (HE) and secondary education (SSC) as a function of the forcing variable. Dashed line shows the treatment probability.

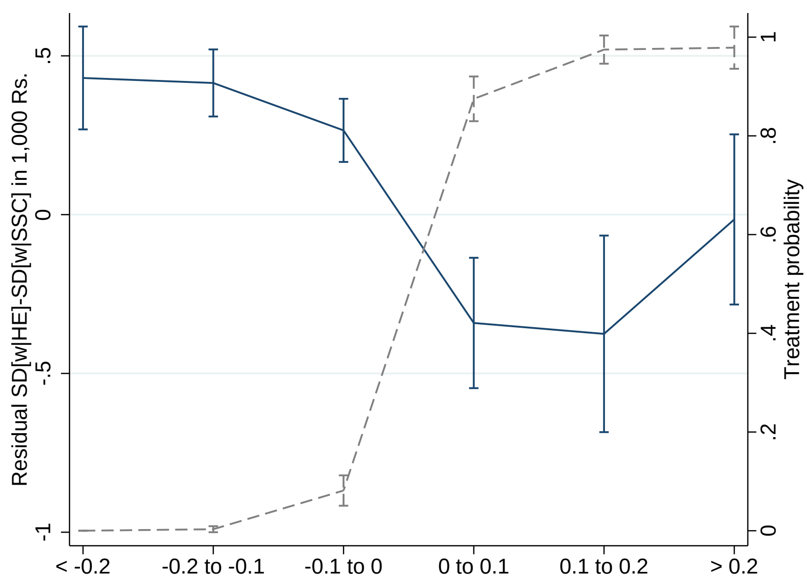

Figure 4: Residual differences (controlling for observables) between the standard deviation in perceived returns to higher (HE) and secondary (SSC) education as a function of the forcing variable. Dashed line shows the treatment probability.

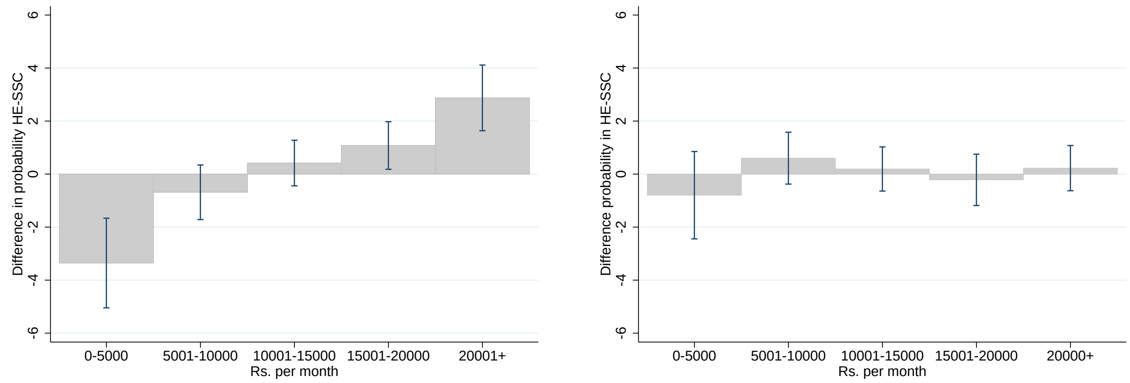

Figure 5: Perceived increase in wage outcomes after completing higher (HE) versus lower secondary education (SSC) for different income bands, after partialling out individual-level characteristics. Left panel corresponds to the direct effect on recipients and non-recipients; right panel shows the indirect effects.

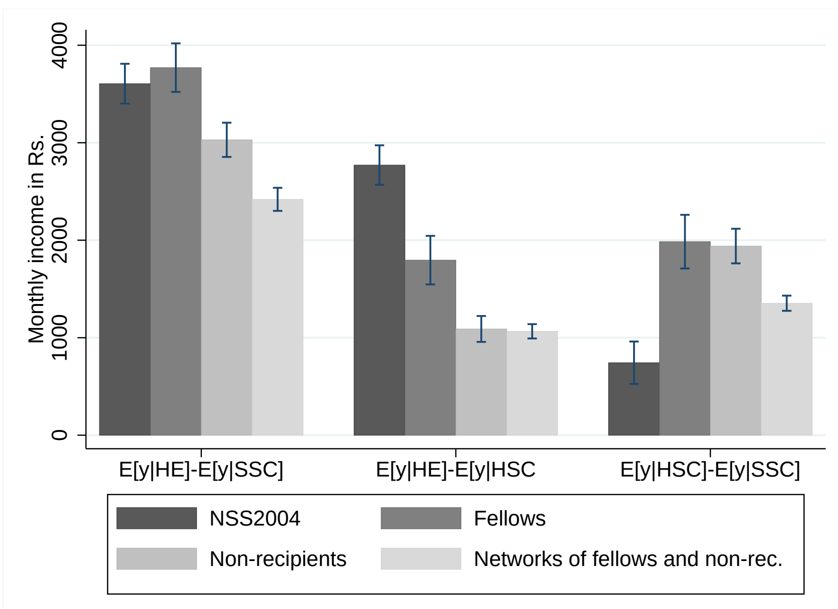

Figure 6: Comparing perceived returns to higher (HE) vs lower secondary education (SSC) with actual Mincerian returns from the Indian National Sample Survey 2004, adjusted for annual inflation between 2004-2008; broken down by perceived gains from higher secondary (HSC) vs lower secondary (SSC) as well as perceived gains from higher (HE) vs higher secondary education (HSC).

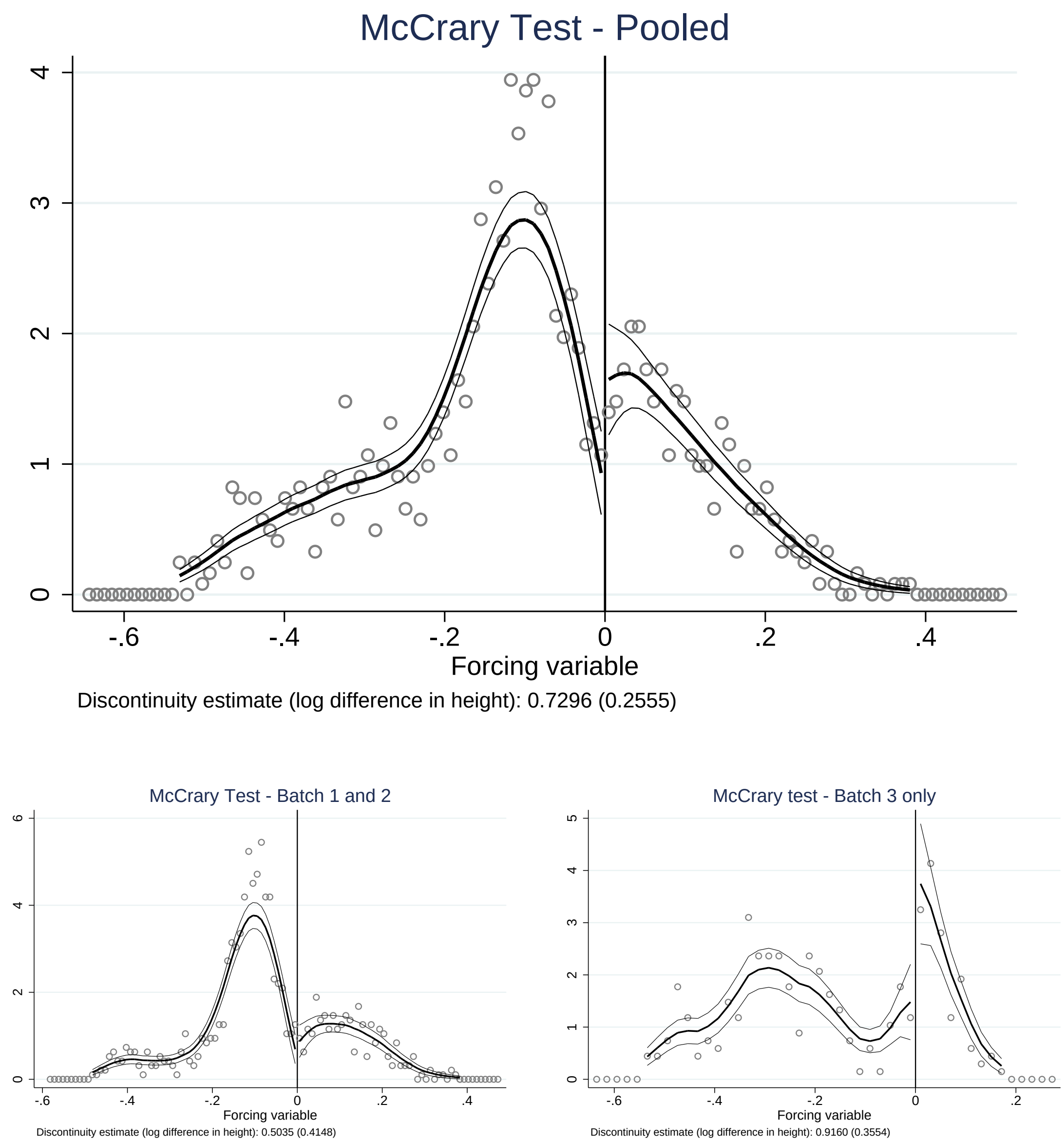

Figure 7: McCrary Test (2008): Testing the null hypothesis of continuity in the density of the forcing variable at the discontinuity point (solid line) for pooled sample as well as excluding the third batch. Standard errors in parentheses.

Table 1: Testing for balanced sample between fellows and non-recipients around the cut-off and across the full sample

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

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

Table 2: Testing for balanced sample between those in the networks of recipients and non-recipients around the cut-off

	Panel A: Characteristics of role models				Panel B: Own characteristics		
Batch 1	Fellows (1)	Non-recipients (2)	Diff (1)-(2)		Fellows (3)	Non-recipients (4)	Diff (3)-(4)
Grade 10 marks	67.05	66.67	0.37				
(N=222)	(0.56)	(0.43)	(0.71)				
Income month	2034.70	2236.3	-201.59	Own house	0.8	0.87	-0.07
(N=215)	(112.17)	(107.27)	(155.21)	(N=218)	(0.04)	(0.02)	(0.05)
Household size	5.83	5.79	0.04	Household size	5.76	5.89	-0.13
(N=218)	(0.13)	(0.14)	(0.20)	(N=218)	(0.14)	(0.15)	(0.21)
Batch 2							
Grade 10 marks	65.09	64.98	0.11				
(N=176)	(0.44)	(0.46)	(0.64)				
Income month	2569.38	2812.82	-243.43	Own house	0.84	0.85	-0.01
(N=162)	(107.51)	(317.19)	(334.92)	(N=176)	(0.03)	(0.04)	(0.05)
Household size	5.44	5.68	-0.23	Household size	6	5.72	0.28
(N=176)	(0.14)	(0.17)	(0.22)	(N=176)	(0.14)	(0.17)	(0.22)
Batch 3							
Grade 10 marks	64.82	65.72	-0.89				
(N=183)	(0.32)	(0.82)	(0.89)				
Income month	2719.14	2408.14	311.001	Own house	0.75	0.71	0.04
(N=171)	(104.94)	(350.01)	(365.41)	(N=181)	(0.03)	(0.06)	(0.07)
Household size	5.75	5.59	0.15	Household size	6.03	5.53	0.49**
(N=183)	(0.13)	(0.17)	(0.22)	(N=181)	(0.15)	(0.16)	(0.22)
Pooled							
Grade 10 marks	65.51	66.00	-0.49				
(N=581)	(0.25)	(0.31)	(0.40)				
Income month	2485.69	2418.16	67.52	Own house	0.79	0.83	-0.04
(N=548)	(64.63)	(120.85)	(137.05)	(N=575)	(0.02)	(0.02)	(0.03)
Household size	5.67	5.71	-0.04	Household size	5.94	5.77	0.07
(N=577)	(0.08)	(0.09)	(0.12)	(N=575)	(0.08)	(0.09)	(0.13)

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

Table 3: Testing equality of distribution in baseline variables

	Testing for equality of distributions	
p-values	Cut-off (1)	All respondents (2)
Batch 1		
Grade 10 marks (N=128)	0.906	0.054*
Income month (N=123)	0.999	0.021**
Household size (N=126)	0.998	1.00
Batch 2		
Grade 10 marks (N=96)	0.620	0.399
Income month (N=89)	0.686	0.459
Household size (N=96)	0.620	0.747
Batch 3		
Grade 10 marks (N=94)	0.753	0.042**
Income month (N=86)	0.161	0.389
Household size (N=94)	1.00	0.996
Pooled		
Grade 10 marks (N=318)	0.380	0.010***
Income month (N=298)	0.210	0.021**
Household size (N=316)	0.862	0.984

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 4: Baseline characteristics of planned and realized sample

	Planned sample (1)	Actual Sample (2)	Diff (1)-(2)
Batch 1			
Grade 10 marks	66.97	67.71	-0.73
(N=514)	(0.35)	(0.36)	(0.51)
Income month	2296.1	2354.73	58.63
(N=504)	(96.68)	(91.47)	(133.10)
Household size	5.64	5.61	0.02
(N=510)	(0.08)	(0.09)	(0.12)
Batch 2			
Grade 10 marks	65.22	65.14	0.07
(N=285)	(0.39)	(0.45)	(0.60)
Income month	2564.54	2573.48	8.93
(N=266)	(151.14)	(143.27)	(208.25)
Household size	5.54	5.41	-0.12
(N=284)	(0.13)	(0.13)	(0.18)
Batch 3			
Grade 10 marks	65.15	65.43	-0.28
(N=296)	(0.39)	(0.41)	(0.57)
Income month	2599.42	2716.87	-117.44
(N=273)	(141.03)	(147.49)	(204.07)
Household size	5.70	5.68	0.02
(N=296)	(0.11)	(0.11)	(0.16)
Pooled			
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)

Notes: Testing for non-response bias in the recipients/non-recipients sample. 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 5: Direct impact of fellowship reward on perceived returns (mean)

	Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	3.424	3.422	3.422	3.422	3.422	3.422
$cutoff$	0.562***	0.541***	0.744***	0.741***	0.706***	0.759***
	(0.13)	(0.13)	(0.24)	(0.24)	(0.24)	(0.26)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.02	0.06	0.06	0.06	0.07	0.07
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	3.424	3.422	3.422	3.422	3.422	3.422
$fellow$	0.673***	0.647***	1.275***	1.258***	1.232***	1.369***
	(0.17)	(0.16)	(0.44)	(0.45)	(0.45)	(0.49)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.04	0.08	0.09	0.10	0.10	0.10
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	3.498	3.498				
$cutoff$	0.682***	0.697***				
	(0.18)	(0.19)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	313	312				
R^2	0.03	0.08				

Notes: The direct impact of the fellowship award on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable taking the value 1 if the student is above the cut-off and 0 otherwise, with control variables and a flexible functional form for the forcing variable. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 6: Direct impact of fellowship reward on perceived returns (SD)

	Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	-0.169	-0.169	-0.169	-0.169	-0.169	-0.169
$cutoff$	-0.653***	-0.659***	-0.631***	-0.643***	-0.634***	-0.645***
	(0.06)	(0.06)	(0.17)	(0.17)	(0.17)	(0.18)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.09	0.13	0.13	0.13	0.13	0.13
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.169	-0.169	-0.169	-0.169	-0.169	-0.169
$fellow$	-0.782***	-0.788***	-1.081***	-1.093***	-1.107***	-1.163***
	(0.08)	(0.08)	(0.23)	(0.23)	(0.24)	(0.28)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.13	0.17	0.17	0.17	0.17	0.17
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	-0.249	-0.249				
$cutoff$	-0.719***	-0.668***				
	(0.10)	(0.10)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	313	312				
R^2	0.09	0.15				

Notes: The direct impact of the fellowship award on the standard deviation of expected wage, as measured by the difference between $SD[HE]$ and $SD[SSC]$ in 1,000 Rs ($16). Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that takes the value 1 if the student is above the cut-off and 0 otherwise, including control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 7: Peer effects on perceived returns (mean) of those in the networks

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$				
Panel A	(1)	(2)	(3)	(4)
	OLS		IV	
Mean of dep. variable	2.419	2.419	2.419	2.419
$cutoff$	0.124	0.185	0.166	0.255
$(fellow)$	(0.14)	(0.14)	(0.19)	(0.19)
Forcing variable	No	No	No	No
Controls	No	Yes	No	Yes
Observations	575	575	575	575
R^2	0.00	0.07	0.00	0.06
Panel B	(5)	(6)	(7)	(8)
	Indirect effect, broken down by network			
	Siblings & Neighbors		Friends	
	OLS	IV	OLS	IV
Mean of dep. variable	2.421	2.421	2.416	2.416
$cutoff$	0.140	0.196	0.241	0.322
$(fellow)$	(0.18)	(0.24)	(0.17)	(0.23)
Controls	Yes	Yes	Yes	Yes
Observations	313	313	262	262
R^2	0.06	0.05	0.09	0.08

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

Table 8: Peer effects on perceived returns (SD) of those in the networks

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

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

Table 9: Peer effects on intention to apply

Dependent variable: Intends to apply for fellowship				
Panel A	(1)	(2)	(3)	(4)
	OLS		IV	
Mean of dep. variable	0.487	0.492	0.487	0.492
$cutoff$	0.139***	0.103**	0.185***	0.141***
$(fellow)$	(0.04)	(0.04)	(0.04)	(0.06)
Forcing variable	No	No	No	No
Controls	No	Yes	No	Yes
Observations	581	575	581	575
R^2	0.01	0.15	0.03	0.16
Panel B	(5)	(6)	(7)	(8)
	Indirect effect, broken down by network			
	Siblings & Neighbors		Friends	
	OLS	IV	OLS	IV
Mean of dep. variable	0.546	0.546	0.417	0.427
$cutoff$	0.110*	0.072	0.222***	0.182**
$(fellow)$	(0.05)	(0.05)	(0.07)	(0.07)
Controls	Yes	Yes	Yes	Yes
Observations	313	313	268	262
R^2	0.01	0.17	0.06	0.14

Notes: Pooled effects on dummy whether peer intends to apply for the fellowship under study, with and without controls (Panel A). Columns (1)-(2) report OLS estimates while Columns (3)-(4) report IV estimates where selection is instrumented by $cutoff$. Panel B reports the peer effects broken down by network type, with and without controls. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). In 1,000 Rs (\$16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Peer effects on knowledge about alternative funding opportunities

Dependent variable: Knowledge about alternative funding				
Panel A	(1)	(2)	(3)	(4)
	OLS		IV	
Mean of dep. variable	0.270	0.273	0.270	0.273
$cutoff$	0.095***	0.084***	0.126***	0.116***
$(fellow)$	(0.03)	(0.03)	(0.04)	(0.04)
Forcing variable	No	No	No	No
Controls	No	Yes	No	Yes
Observations	581	575	581	575
R^2	0.01	0.40	0.03	0.40
Panel B	(5)	(6)	(7)	(8)
	Indirect effect, broken down by network			
	Siblings & Neighbors		Friends	
	OLS	IV	OLS	IV
Mean of dep. variable	0.150	0.150	0.410	0.419
$cutoff$	0.003	0.026*	0.261***	0.206**
$(fellow)$	(0.03)	(0.01)	(0.07)	(0.08)
Controls	Yes	Yes	Yes	Yes
Observations	313	313	268	262
R^2	0.00	0.80	0.05	0.09

Notes: Pooled effects on dummy whether peer knows at least 1 alternative funding source (other than the fellowship under study), with and without controls (Panel A). Columns (1)-(2) report OLS estimates while Columns (3)-(4) report IV estimates where selection is instrumented by $cutoff$. Panel B reports the peer effects broken down by network type, with and without controls. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). In 1,000 Rs ($16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Peer effects on knowledge about fellowship

Dependent variable: Knowledge about fellowship				
Panel A	(1)	(2)	(3)	(4)
	OLS		IV	
Mean of dep. variable	0.195	0.195	0.195	0.195
$cutoff$	0.047***	0.036**	0.063***	0.050**
$(fellow)$	(0.01)	(0.01)	(0.02)	(0.02)
Forcing variable	No	No	No	No
Controls	No	Yes	No	Yes
Observations	575	575	575	575
R^2	0.01	0.14	0.03	0.16
Panel B	(5)	(6)	(7)	(8)
	Indirect effect, broken down by network			
	Siblings & Neighbors		Friends	
	OLS	IV	OLS	IV
Mean of dep. variable	0.214	0.214	0.171	0.171
$cutoff$	0.023	0.032	0.051**	0.068**
$(fellow)$	(0.02)	(0.02)	(0.02)	(0.03)
Controls	Yes	Yes	Yes	Yes
Observations	313	313	262	262
R^2	0.20	0.20	0.09	0.11

Notes: Pooled effects on knowledge about the fellowship measured by a composite score between 0 (lowest) and 1 (highest) for peers around the cut-off, with and without controls (Panel A). Columns (1)-(2) report OLS estimates while Columns (3)-(4) report IV estimates where selection is instrumented by $cutoff$. Panel B reports the peer effects broken down by network type, with and without controls. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the role model level (fellow/non-recipient). In 1,000 Rs ($16). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Impact of fellowship reward on perceived returns: Own vs. others

	Dependent variable: $E_i[y\|HE]$ for own and others					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
	Own expected wage			Expected wage for others		
Mean of dep. var.	8.595	8.593	8.593	10.454	10.431	10.431
$cutoff$	0.670***	0.567***	0.512**	0.482	0.641	0.403
	(0.12)	(0.21)	(0.24)	(0.37)	(0.89)	(0.94)
Forcing	No	Linear	Quartic	No	Linear	Quartic
Controls	No	Yes	Yes	No	Yes	Yes
Observations	514	512	512	461	459	459
R^2	0.03	0.08	0.09	0.00	0.03	0.04
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
	Own expected wage			Expected wage for others		
Mean of dep. var.	8.595	8.593	8.593	10.454	10.431	10.431
$fellow$	0.802***	0.972***	0.923***	0.563	0.937	0.620
	(0.16)	(0.37)	(0.44)	(0.43)	(1.23)	(1.39)
Forcing	No	Linear	Quartic	No	Linear	Quartic
Controls	No	Yes	Yes	No	Yes	Yes
Observations	514	512	512	461	459	459
R^2	0.05	0.11	0.11	0.00	0.03	0.031
Panel C	(13)	(14)		(15)	(16)	
	Restricted sample around the cut-off					
	Own expected wage			Expected wage for others		
Mean dep. var.	8.629	8.625		10.401	10.363	
$cutoff$	0.689***	0.616***		0.362	0.125	
	(0.17)	(0.16)		(0.53)	(0.61)	
Forcing variable	No	No		No	No	
Controls	No	Yes		No	Yes	
Observations	313	312		281	280	
R^2	0.03	0.11		0.00	0.04	

Notes: Perceived returns for higher education graduates: Dependent variable is i) the own expected wage (level) for HE ii) the expected HE wage (level) for other graduates, in 1,000 Rs ($16), estimated using a sharp regression discontinuity design (Panel A) and fuzzy regression discontinuity design (Panel B), adding controls and allowing for flexible control of the forcing variable. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. $cutoff$ is an indicator variable that is 1 if the role-model of the student is above the cut-off and 0 otherwise. Robust standard errors in parentheses, clustered at the school-level.

Table 13: Impact of fellowship reward on number of people encouraged to apply

Dependent variable: Log(1+Number of people encouraged to apply)						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Sharp Regression Discontinuity (OLS)					
Mean of dep. var.	1.311	1.310	1.310	1.310	1.310	1.310
$cutoff$	0.624***	0.628***	0.333**	0.331**	0.311**	0.315**
	(0.07)	(0.07)	(0.13)	(0.13)	(0.12)	(0.13)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	467	464	464	464	464	464
R^2	0.12	0.13	0.14	0.14	0.15	0.15
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	1.311	1.310	1.310	1.310	1.310	1.310
$fellow$	0.746***	0.752***	0.565***	0.555***	0.530***	0.547***
	(0.09)	(0.09)	(0.19)	(0.19)	(0.19)	(0.21)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	467	464	464	464	464	464
R^2	0.19	0.21	0.20	0.20	0.20	0.20
Panel C	(13)	(14)	(15)	(16)	(17)	(18)
	Fuzzy Regression Discontinuity (IV), broken down by network					
	Pooled	Siblings	Relatives	Neighbors	Friends	Juniors
Mean dep. var.	1.310	0.103	0.118	0.286	0.710	0.479
$fellow$	0.546***	0.024	0.126	0.174	0.367*	0.097
	(0.20)	(0.06)	(0.10)	(0.140)	(0.23)	(0.26)
Forcing variable	Quartic	Quartic	Quartic	Quartic	Quartic	Quartic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	464	464	464	464	464	464
R^2	0.20	0.06	0.08	0.07	0.04	0.12

Notes: Impact of fellowship award on the (log) number of students encouraged, estimated using a sharp regression discontinuity design (Panel A) and fuzzy regression discontinuity design (Panel B), adding controls and allowing for flexible control of the forcing variable. Panel C breaks down the pooled sample by network type. Robust standard errors in parentheses, clustered at the school-level.

Table 14: Robustness check: Perceived returns - Alternative measure I

Dependent variable: $[Pr(y_{max}\|HE) - Pr(y_{min}\|HE)] - [Pr(y_{max}\|SSC) - Pr(y_{min}\|SSC)]$						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Sharp Regression Discontinuity (OLS)					
Mean of dep. var.	29.217	29.198	29.198	29.198	29.198	29.198
$cutoff$	4.979***	4.842***	6.063***	6.040***	5.876***	6.404***
	(1.06)	(1.02)	(1.88)	(1.95)	(1.97)	(2.10)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.02	0.07	0.07	0.07	0.07	0.07
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	29.217	29.198	29.198	29.198	29.198	29.198
$fellow$	5.961***	5.792***	10.388***	10.253***	10.255***	11.544***
	(1.30)	(1.23)	(3.34)	(3.33)	(3.32)	(3.66)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.04	0.09	0.10	0.10	0.10	0.10
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	29.933	29.933				
$cutoff$	5.912***	5.970***				
	(1.59)	(1.51)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	313	312				
R^2	0.03	0.08				

Notes: In this table we present results on the impact of the fellowship award on the variance 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%). Depending on specification, we treatment variable is either $cutoff$ (OLS, and Cut-off) or $fellows$, instrumented by $cutoff$ (IV).

Table 15: Robustness check: Perceived returns - Alternative measure II

Dependent variable: Signal to Noise Ratio $E[y\|HE]/SD[y\|HE] - E[y\|SSC]/SD[y\|SSC]$						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Sharp Regression Discontinuity (OLS)					
Mean of dep. var.	0.080	0.080	0.080	0.080	0.080	0.080
$cutoff$	0.033***	0.033***	0.037***	0.037***	0.036***	0.038***
	(0.004)	(0.004)	(0.009)	(0.01)	(0.01)	(0.11)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.05	0.08	0.08	0.08	0.08	0.09
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean of dep. var.	0.080	0.080	0.080	0.080	0.080	0.080
$fellow$	0.039***	0.039***	0.063***	0.062***	0.063***	0.069***
	(0.006)	(0.006)	(0.01)	(0.01)	(0.01)	(0.01)
Forcing	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	512	512	512	512
R^2	0.09	0.12	0.13	0.13	0.13	0.13
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	0.085	0.085				
$cutoff$	0.039***	0.038***				
	(0.007)	(0.007)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	313	312				
R^2	0.06	0.10				

Notes: In this table we present results on the 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, we treatment variable is either $cutoff$ (OLS, and Cut-off) or $fellows$, instrumented by $cutoff$ (IV).

Table 16: Robustness check: Perceived returns (mean), monotone only

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$ - **Monotone only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
			Sharp Regression Discontinuity (OLS)			
Mean dep. var.	3.357	3.357	3.357	3.357	3.357	3.357
$cutoff$	0.523***	0.476***	0.624**	0.603**	0.544***	0.582**
	(0.17)	(0.16)	(0.27)	(0.27)	(0.27)	(0.29)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.02	0.06	0.06	0.06	0.06	0.06
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
			Fuzzy Regression Discontinuity (IV)			
Mean dep. var.	3.357	3.357	3.357	3.357	3.357	3.357
$fellow$	0.631***	0.574***	1.080***	1.031***	0.960*	1.059***
	(0.21)	(0.19)	(0.49)	(0.49)	(0.50)	(0.53)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.03	0.08	0.09	0.09	0.09	0.09
Panel C	(13)	(14)				
			Restricted sample around the cut-off			
Mean dep. var.	3.443	3.443				
$cutoff$	0.726***	0.724***				
	(0.23)	(0.23)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	243	243				
R^2	0.03	0.08				

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, $E_i[y|HE] - E_i[y|SSC]$. Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that is 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 17: Robustness check: Perveived returns (SD), monotone only

Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$ - **Monotone only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
$cutoff$	-0.644***	-0.633***	-0.559***	-0.567***	-0.561***	-0.555***
	(0.08)	(0.08)	(0.20)	(0.21)	(0.21)	(0.21)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.08	0.14	0.14	0.14	0.14	0.14
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.148	-0.148	-0.148	-0.148	-0.148	-0.148
$fellow$	-0.777***	-0.763***	-0.967***	-0.970***	-0.988***	-1.009***
	(0.10)	(0.09)	(0.28)	(0.28)	(0.30)	(0.32)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396
R^2	0.13	0.18	0.18	0.18	0.18	0.18
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	-0.223	-0.223				
$cutoff$	-0.729***	-0.664***				
	(0.13)	(0.13)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	243	243				
R^2	0.09	0.16				

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 $SD[HE]$ and $SD[SSC]$ in 1,000 Rs ($16). Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that is 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 18: Robustness check: Alternative construction of perceived returns

Dependent variable: $E[w\|HE] - E[w\|SSC]$ - **Alternative construction**						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Sharp Regression Discontinuity (OLS)					
	Lower		Upper		Middle	
Mean of dep. Variable	3.424	3.422	3.425	3.423	3.425	3.422
$cutoff$	0.562***	0.759***	0.562***	0.765***	0.562***	0.762***
	(0.13)	(0.26)	(0.13)	(0.26)	(0.13)	(0.26)
Forcing	No	Quartic	No	Quartic	No	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	514	512	512	512
R^2	0.02	0.07	0.02	0.07	0.02	0.07
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B	Fuzzy Regression Discontinuity (IV)					
	Lower		Upper		Middle	
Mean of dep. Variable	3.424	3.422	3.425	3.423	3.425	3.422
$fellow$	0.673***	1.369***	0.673***	1.379***	0.673***	1.374***
	(0.17)	(0.49)	(0.17)	(0.49)	(0.17)	(0.49)
Forcing	No	Quartic	No	Quartic	No	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	514	512	514	512	512	512
R^2	0.04	0.10	0.04	0.10	0.04	0.10
Panel C	(13)	(14)	(15)	(16)	(17)	(18)
	Restricted sample around the cut-off					
	Lower		Upper		Middle	
Mean dep. var.	3.424	3.422	3.425	3.423	3.425	3.422
$cutoff$	0.682***	0.697***	0.681***	0.698***	0.682***	0.698***
	(0.18)	(0.19)	(0.18)	(0.19)	(0.18)	(0.19)
Forcing variable	No	No	No	No	No	No
Controls	No	Yes	No	Yes	No	Yes
Observations	313	312	313	312	313	312
R^2	0.03	0.08	0.03	0.08	0.03	0.08

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 direct impact of the fellowship award on the standard deviation of expected wage, as measured by the difference between $SD[HE]$ and $SD[SSC]$ in 1,000 Rs ($16). Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that takes the value 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 19: Robustness check: Perceived returns (Mean), excluding batch 3

Dependent variable: $E_i[y\|HE] - E_i[y\|SSC]$ - **Batch 1 & 2 only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	3.379	3.375	3.375	3.375	3.375	3.375
$cutoff$	0.543***	0.531***	0.990***	0.990***	1.008***	1.006***
	(0.15)	(0.16)	(0.28)	(0.28)	(0.31)	(0.32)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.02	0.05	0.06	0.06	0.06	0.06
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	3.379	3.375	3.375	3.375	3.375	3.375
$fellow$	0.606***	0.591***	1.332***	1.327***	1.463*	1.506***
	(0.17)	(0.18)	(0.44)	(0.43)	(0.50)	(0.55)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	396	367	367	367	367	367
R^2	0.03	0.06	0.08	0.08	0.08	0.07
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	3.381	3.375				
$cutoff$	0.758***	0.785***				
	(0.22)	(0.25)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	219	218				
R^2	0.04	0.07				

Notes: In this table we test the robustness of our main results to the exclusion of batch 3, for which we reject the McCrary test of the absence of endogenous sorting around the cut-off. We measure the direct impact of the fellowship award on perceived returns to education, as measured by the expected gain in 1,000 Rs ($16) from completing HE vis-a-vis SSC, $E_i[y|HE] - E_i[y|SSC]$. Panel A shows the results using a sharp regression discontinuity design where $cutoff$ is an indicator variable that is 1 if the student is above the cut-off and 0 otherwise, adding control variables and allowing the forcing variable to take a flexible functional form. Panel B shows the results using a fuzzy regression discontinuity design, where actual fellowship award ($fellow$) is instrumented by $cutoff$. Panel C restricts the sample to observations within an interval of 0.1 score points around the cut-off. 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 20: Robustness check: Perceived returns (SD), excluding batch 3

Dependent variable: $SD_i[y\|HE] - SD_i[y\|SSC]$ - **Batch 1 & 2 only**						
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Sharp Regression Discontinuity (OLS)					
Mean dep. var.	-0.084	-0.083	-0.083	-0.083	-0.083	-0.083
$cutoff$	-0.657***	-0.665***	-0.722***	-0.731***	-0.690***	-0.678***
	(0.07)	(0.07)	(0.21)	(0.20)	(0.20)	(0.22)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.10	0.13	0.13	0.14	0.14	0.14
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
	Fuzzy Regression Discontinuity (IV)					
Mean dep. var.	-0.084	-0.083	-0.083	-0.083	-0.083	-0.083
$fellow$	-0.734***	-0.740***	-0.972***	-0.979***	-1.002***	-1.016***
	(0.07)	(0.07)	(0.21)	(0.20)	(0.23)	(0.26)
Forcing variable	No	No	Linear	Quadratic	Cubic	Quartic
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	368	367	367	367	367	367
R^2	0.13	0.16	0.16	0.17	0.16	0.16
Panel C	(13)	(14)				
	Restricted sample around the cut-off					
Mean dep. var.	-0.091	-0.091				
$cutoff$	-0.710***	-0.692***				
	(0.12)	(0.12)				
Forcing variable	No	No				
Controls	No	Yes				
Observations	219	218				
R^2	0.11	0.15				

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