ESSAYS ON HUMAN CAPITAL & DEVELOPMENT IN INDIA

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ESSAYS ON HUMAN CAPITAL & DEVELOPMENT

IN INDIA

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This dissertation consists of three independent research papers, tied under a broad research agenda of "human capital" in India. Chapters 1 and 2 are closely related and both utilize a self-collected, primary dataset on the subjective beliefs, of a sample of 12th grade students, regarding factors that may influence their decision to invest in post-secondary education. Chapter 3 examines a different dimension of human capital and investigates the role of agriculture in improving the nutritional status of rural, Indian women.

In the first paper, I examine the inaccuracy of students' beliefs regarding the labor market returns (i.e. wage earnings) associated with post-secondary (college) education. Towards this end, I randomize information on measured population wages to a sample of 12th grade students, drawn from schools affiliated with a large public state university in India, who at the time were roughly six months away from making a decision regarding college attendance and college track (technical, academic, vocational) conditional on attendance. I find that, at baseline, students beliefs about population earnings deviate substantially from true earnings in the population. Upon the receipt of potentially new information, students revise beliefs regarding own-wages in the direction of the information, though the average extent of updating is small

and masks substantial sub-group heterogeneity. Additionally, subsequent changes in enrollment intentions and intentions to borrow for higher education are in line with both the extent and direction of wage belief updating. A portion of the heterogeneity in wage belief updating can be explained by initial misperceptions regarding population earnings, and baseline relevance of earnings to enrollment intentions. Yet a large portion remains unexplained, consistent with wide heterogeneity in updating heuristics, at the individual level. From a policy standpoint, these findings point to the limited capacity of information campaigns based on population-level aggregates to induce, on average, large changes in individual priors and help to rationalize a number of recent papers that find heterogeneous impacts of information provision on education outcomes.

In my second paper, I draw descriptive insights about the extent and implications of the same sample of 12th grade students' misperceptions about post-secondary (college) expenses, elicited 5-9 months prior to them completing high school. Students' subjective beliefs about post-secondary expenses are compared to a reference distribution of actual expenses incurred by students of post-secondary education. Students overestimate expenses for two out of three tracks. I estimate that if students perceived expenses more accurately, then their perceived affordability for technical tracks and general tracks would increase by 10 percentage points and 55 percentage points, respectively. Students' have relatively more accurate beliefs about the expenses associated with their utility maximizing track or their most preferred track, which I estimate using a flexible model of track-choice. Nevertheless, I show that purging cost beliefs of errors, also increases the perceived affordability of students'

preferred tracks by an economically and statistically large magnitude.

My third paper is co-authored with Dr. Prabhu Pingali. In this paper, we establish a statistically important relationship between household agricultural income and maternal BMI using a five-year panel dataset of agricultural households drawn from 18 villages across five Indian states. Using within household variation over time, we estimate both, the extent to which short-term changes in agricultural income are associated with short-term changes in BMI, and the effect of agricultural income growth on BMI growth over a longer term. Over the longer term, and for the group of households that regularly farm, we find a 10 pp. agriculture income growth to be associated with a 0.15 pp. growth in BMI. Consistent with the literature, this effect is economically modest, but important considering that we do not find a corresponding effect for growth in non-agricultural income. We present evidence to suggest that the own-production of food is not an important pathway for nutritional improvements, but the agricultural income effect is likely operational through purchase of food, specifically of protein rich pulses. Effects of agricultural income are stronger for younger women, in the age-group 15-25 years, who face a particularly strong nutritional disadvantage in India.

BIOGRAPHICAL SKETCH

Tanvi Rao was born in Hyderabad, India, and grew up in the bustling metropolis and national capital of New Delhi. She was schooled at Sardar Patel Vidyalaya (SPV), where she studied for 14 years, from nursery up until the 12th grade. Despite attending other excellent institutes thereafter, she considers her formative years spent at SPV, to have had the strongest and most profound impact on her. In many different but reinforcing ways, SPV emphasized the importance of being thoughtful, compassionate and emotionally intelligent, in addition to thinking creatively and critically in all subjects of educational pursuit. While other competing high-schools in the city pushed students into the hard sciences or business post 10th grade, SPV encouraged students into humanities and had an excellent humanities department. It was here, in the final years of high-school, that Tanvi's interest in economics, specifically development economics, was fostered. Tanvi then attended the Shri Ram College of Commerce (SRCC), part of Delhi University, for an undergraduate degree in economics. Here, she studied among the nation's highest scoring students, and learnt the basics of economics and statistics. A short stint at the London School of Economics (LSE), during undergrad, introduced Tanvi to econometrics, which today aides her in all of her academic inquiries. Tanvi was introduced to the demands and delights of academic research in economics only once she started her M.S. program in the department of Applied Economics and Management (AEM) at Cornell University, which she joined in the fall of 2010, the same year she completed her undergraduate education. Cornell and Ithaca soon became home and a two year masters degree, led to her staying on for an additional five years of doctoral training in the department.

Even though seven years of graduate school may seem like a long time, each year brought with it a unique set of challenges, learning, getting to a milestone or starting over, and the years passed by, in what today feels, to her, like a blink of an eye. While most aspects of doing research are rewarding and fulfilling, enriched further by interaction with outstanding peers and professors, Tanvi particularly enjoyed spending a year in the field, collecting primary data for her dissertation, from high school students in Jharkhand, India, about their beliefs and intentions regarding further education. The defining role of Tanvi's own educational experiences in shaping the course of her life thus far, affirmed her academic interests in studying the education decisions of other, more resource constrained, Indian students. During field work, time spent outside of the four walls of the university strengthened learning within them, making for a more complete and satisfying graduate school experience.

For my anchors, cheerleaders & role models: Sunil Tadepalli & Shalini Rajaram

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I am extremely grateful to the TATA-Cornell Institute for Agriculture and Nutrition (TCi) for support in numerable ways throughout the course of my Ph.D. Firstly, I thank TCi for generous funding, to collect the primary dataset that forms the basis of inquiry for the majority of my dissertation. Apart from funding, I also received incredible institutional support, both from TCi support staff in India and TCi administrative staff (particularly Mary Catherine French) at Cornell, which ensured the smooth completion of my data collection work. I am also thankful for the opportunity to work as a research assistant with TCi director Dr. Prabhu Pingali for multiple summers and semesters at Cornell, during which time I worked on research which forms a part of my dissertation, and other research which is either published or in line for publication. In TCi, I also found many incredibly supportive peers, a research group to call home, and several opportunities for personal and professional growth.

Several individuals in India made my field work an enjoyable and invaluable experience. Here, I would first like to thank the program manager of my field-project, Mr. Thangkhanlal Thangsing (Lal), whose incredible commitment to the project helped navigate several difficult situations on ground and kept the project on track. I also

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I made several good friends at Cornell, with whom I hope to share many more life experiences. I am particularly grateful for my closest friend circle–Vidhya, Leah, Shouvik, and Maysoon, who cheered me on at every step of the PhD journey. Along with my incredibly supportive and loving parents, I also thank my entire family (in the U.S. and in India) for always lending me a ear and a hand. Lastly, I thank Cornell for Oleg and Oleg for (the) Cornell (experience)–in the five years that passed between being friends and becoming spouses–you made me a better researcher, thinker, and person.

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CHAPTER 1

INFORMATION, HETEROGENEOUS UPDATING & HIGHER EDUCATION DECISIONS: EXPERIMENTAL EVIDENCE FROM INDIA

1.1 Introduction

Providing information on the returns to education in the labor market is generally seen as a powerful demand-side tool to encourage human capital accumulation. The hypothesis that parents and their children might underestimate sizeable returns to education in the labor market, and hence under invest in education, makes information provision a compelling and cost-effective intervention. Encouraging results from Nguyen (2008) & Jensen (2010), who find that randomizing information to a sample of students increased average schooling attainment and school attendance at a basic level of schooling, have spurred a significant literature examining information interventions in education. A substantial focus of the recent literature (Oreopoulos and Dunn (2013); Wiswall and Zafar (2015*b*); Hastings, Neilson and Zimmerman (2015); Pekkala Kerr et al. (2015)) has been in the context of post-secondary education, where premiums vary dramatically by degree and institution, and the focus of policy-makers has been to minimize the extent to which misinformation may lead to sub-optimal decisions, which includes enrollment on account of over estimating the net-returns to certain degree-college tracks vis-a-vis others.

By and large, the emergent literature on information interventions in education has been equivocal in it's findings. While some studies do find information to be effective on average[1], others document only a subset of the overall sample responding to the information in some manner, or not at all (Fryer Jr (2013); Loyalka et al. (2013); Avitabile and De Hoyos Navarro (2015); Pekkala Kerr et al. (2015); Bonilla, Bottan and Ham (2016)). Low average effectiveness of information interventions have mostly been explained by examining why certain groups of individuals may not be able to act on newly acquired information. For instance, Fryer Jr (2013) suggests that information on returns may have increased students intrinsic effort to do better but not real outcomes like test-scores because students may not know how to translate effort into output. In the context of a similar model, Avitabile and De Hoyos Navarro (2015) also find better learning outcomes among high-income individuals, on account of being exposed to information, as these individuals are plausibly in a better position to translate effort into output. Affordability/credit constraints have also been suggested to be binding in Bonilla, Bottan and Ham (2016) who find only a response on the intensive margin of enrollment (towards more selective tracks), driven by the relatively richer sub-group.

In this paper, I offer another explanation for why the provision of population-level information on returns may lead to highly heterogeneous (final) outcomes, by exam-

[1]For instance Oreopoulos and Dunn (2013) find that providing information on mean earnings differences between those who complete high school and those who have college degrees along with access to a financial aid calculator, leads students to revise upwards the expected earnings from college relative to high school and makes them more likely to state college attendance. Hastings, Neilson and Zimmerman (2015) provide highly customized degree and institution specific information to individuals, adapted to their individual enrollment intentions, and find low SES individuals to enroll in degrees with higher net earnings.

ining in detail the first-link in the causal chain that links population-level information to education outcomes, that is, the extent to which individuals update own-earnings beliefs in response to receiving information about population-level averages. Heterogeneity in this case depends on (a) the extent to which individuals are misinformed about population earnings to begin with and (b) the degree to which new information on population earnings is *relevant* to individual's own earnings beliefs. By and large papers in the literature either do not systematically collect information on the impact of information on own belief updating (Fryer Jr (2013);Pekkala Kerr et al. (2015)) or do not establish heterogeneous outcomes between sub-groups over and above homogeneous updating in own-beliefs (Loyalka et al. (2013); Avitabile and De Hoyos Navarro (2015); Bonilla, Bottan and Ham (2016)).

In a framed field experiment (Harrison and List (2004)), I study the role of information provision on own-earnings beliefs, stated enrollment and borrowing intentions, in a setting which abstracts away from both affordability and eligibility constraints. More specifically, I examine the impact of an experiment that provides information to high-school students on the distribution of post-secondary, track-specific population earnings. The impact of the experiment is measured by students updating of own wage beliefs contingent on pursuing each post-secondary track, and their stated probability of enrollment across tracks. Borrowing intentions are measured for higher-education attendance and are not elicited as a track-specific decision. Wage beliefs and enrollment intentions were elicited for (potentially) hypothetical choice-sets where all tracks were available to all individuals. Surveyed students were 5-9

months away from making an actual post-secondary education enrollment decision and were therefore likely to be thinking more actively about their post-secondary education status. The experiment was carried out with 12th grade students drawn from constituent schools of a large, public, state university in India and provided earnings information conditional on three post-secondary tracks- technical, general, vocational- and information conditional on not pursuing post-secondary education.

Students in this sample have substantially biased beliefs about population earnings at baseline[2]. Moreover, at baseline, earnings are a statistically important determinant of enrollment intentions. Despite this the average impact of information provision is small. This is the case even when commonly cited binding constraints like credit availability and eligibility for enrollment are not directly constraining students. In the current setting, the small average impact of information on own-wage belief updating and hence subsequent decisions, stems from highly heterogeneous updating of own-wage beliefs. Heterogeneity is examined by students' current subject stream of study, an important predictor of post-secondary education in the Indian context and also the dimension along which the survey sample was stratified. For one group of students (students in Arts/Humanities) own-wage belief updating, changes in enrollment intentions and treatment-control differences in borrowing intentions are all statistically insignificant. The second group of students (students in the Commerce stream), revise own-earnings beliefs for attendance tracks, relative to non-attendance,

[2]While I do not examine the formation of earnings expectations here, Maertens (2011) indicates that in her sample from rural India, individuals' information sets regarding earnings are positively influenced by the frequency with which information is received via media outlets and from schools, on the number of educated people known and on the respondent's own education.

downwards by a large and highly statistically significant magnitude. This is driven by a large, downward revisions for wage-beliefs conditional on attendance tracks and no statistically significant revision for beliefs conditional on the non-attendance track. This group of students state lower likelihood of enrollment relative to non-enrollment and treatment individuals are not any more likely to borrow than control ones. The final group of students (students in the Science stream), revise own-earnings beliefs for attendance tracks, relative to non-attendance, *upwards*, and this is driven by a large, downward revision for the non-attendance track and no statistically discernible updating for the attendance tracks. This group of students state higher likelihood of enrollment relative to non-enrollment and treatment individuals are much more likely to borrow than control ones. Therefore, two sub-groups of students, Commerce and Science, update attendance earnings, relative to non-attendance, in opposite directions. These patterns are indicative of systematic updating behavior because enrollment and borrowing intentions for the two sub-groups are in line with the direction of wage belief updating. Moreover, within these sub-groups, the same set of individuals seem to be driving both wage belief updating and revisions regarding enrollment intentions.

What explains this differential updating on account of the receipt of the same information? Arts students have at baseline a small and statistically insignificant elasticity of enrollment to wage beliefs. At baseline they also make smaller errors, on average, with regards to beliefs about population earnings. However, these factors do not explain differential updating on the part of Commerce & Science students.

Ex-ante, these students have a statistically important and similar in magnitude elasticity of enrollment to wage beliefs- therefore earnings likely play an important role in their decisions for future education. Importantly, I establish that differential updating for these two groups of students cannot be established on account of differences in baseline errors, regarding population wages, between the groups. Both groups of students have statistically identical baseline errors for all four tracks. This indicates that at the individual level heuristics relating beliefs regarding population earnings to own-earnings are highly varied and undermine the extent to which information campaigns based on population aggregates might be effective on average. Consistent with predictions of belief-based models of Bayesian updating, I find some suggestive evidence to support that individuals with stronger likelihoods to pursue a track are less likely to update earnings beliefs for that track, compared to individuals with weaker likelihoods at baseline. However, in the absence of data on individuals' variance of their prior beliefs, I cannot rule out that a portion of the non-response to information may also be non-Bayesian in nature. However, some insights from the literature indicate that this is a possibility. Wiswall and Zafar (2015*b*), examine the extent to which individual-level updating of beliefs deviates from the Bayesian benchmark. Given each individual's prior belief and variance of their prior belief, they construct a Bayesian benchmark for every individual and then use data on their actual posteriors to classify deviants from the benchmark. They document a wide range of updating heuristics among respondents; nearly a fifth of their sample comprises of "Non-Updaters", in the non-Bayesian sense. Among those who update, while the most common heuristic is within the band of Bayesian updating, a sub-

stantial portion of the sample is more Conservative in their updating and up to 12-19 percent of the respondents update in the Opposite ("Contrary") direction.

To summarize, in this paper, I establish that heterogeneity in the updating of own-wage beliefs in response to population-level information is important and drives significant differences in decision-making between sub-groups in the sample. A large part of this updating is unexplained by initial differences in misperceptions regarding population earnings. Some suggestive evidence indicates that this differential behavior is consistent with predictions of the Bayesian model, but we cannot rule the extent to which non-Bayesian behavior may account for these findings. However the literature suggests that the latter is likely to play an important role and merits further investigation. In this paper, reference to differential updating heuristics indicates both variation in updating consistent with the Bayesian model (i.e. on account differential variance of prior beliefs) and non-Bayesian updating.

Campaigns designed to provide earnings information based on population level aggregates are attractive to policy-makers. For instance, based on Jensen (2010)'s influential study, the Mexican Secretariat of Public Education implemented an intervention to provide students entering 10th grade with information about the returns to high-school and tertiary education, with an aim to improve on-time graduation and learning outcomes (Avitabile and De Hoyos Navarro (2015)). A major appeal to information interventions are also their potential for being cost-effective[3]. For

[3]Cost-effectiveness analysis accessed on J-PAL's website at: https://www.povertyactionlab.org/policy-lessons/education/improving-student-participation show that information provision is more cost-effective than merit scholarships and cash transfers.

a policy-maker looking to implement an information campaign to encourage more optimal education decision making, these findings are not encouraging because they highlight that the heterogeneity by which individuals apply population-level information as relevant to themselves is important. Therefore, even if a policy-maker has accurate knowledge about the direction and magnitude of baseline errors regarding population wages, for a particular group, they may not be able to induce large changes, on average, in individual's beliefs about themselves. More detailed data on earnings conditional on different types of education (as is available in Chile (Hastings, Neilson and Zimmerman (2015)), Finland (Pekkala Kerr et al. (2015)) & Colombia (Bonilla, Bottan and Ham (2016)) and for different groups of individuals (like the National Survey of College Graduates in the U.S.) may help in the design of more specific information interventions which may provide more informative signals to different groups of individuals. However, currently, in most developing countries, such information is not systematically collected.

The primary contribution of this study is to the literature that evaluates the potential of information policies and campaigns to influence education decision-making. However, it's findings can also throw light in other areas of economics where aggregate information is used to influence individual decision-making. Some examples include the use of information in impacting occupation choice (Osman (2014)), sexual-behaviors (Dupas (2011)) and migration decisions (Shrestha (2016)). The results on the demand for borrowing as a result of information provision in this paper, speak to an important strand in the large literature on higher education ac-

However, only one study on information provision is used as reference

cess, which focuses on borrowing constraints (Stinebrickner and Stinebrickner (2008); Delavande and Zafar (2014); Kaufmann (2014)). In principal, individuals who would like to borrow at the going interest-rate but are unable to gain credit are classified to be credit-constrained. However, being credit-constrained depends on each individuals net-return calculation from education, which itself may suffer from information gaps. In my study, the fraction of the sample which revises expected earnings from post-secondary attendance, relative to non-attendance, upwards is also more likely to state an increased intentions to borrow. Therefore, to the extent that the link between information provision and own-wage beliefs is present, information can affect behavior to lift more binding barriers to education access.

The rest of the paper is organized as follows: section 1.2 briefly discusses aspects of post-secondary education in India, section 1.3 outlines a conceptual framework to motivate sources of heterogeneity in own-wage belief updating, section 1.4 discusses data and experimental details, section 1.5 is devoted to results, section 1.6 entails a discussion on factors that explain (or fail to) heterogeneous updating in the sample and the final section concludes.

1.2 Post-Secondary Education in India

I study the decision-making of students between three post-secondary tracks and the non-attendance alternative. After the completion of high school, students choose whether or not to attend post-secondary education and what type of post-secondary

education to enroll in. I classify post-secondary education into three "attendance tracks"- technical/professional degrees, general academic degrees and vocational diploma or certificate courses. This is also how the Government of India classifies higher education tracks in its collection of post-secondary education data as part of the National Sample Surveys (NSS) and this is the lowest level of aggregation at which nationally representative earnings data is available in India.

Each higher education track studied in this paper lies at distinct points of the net-return spectrum from post-secondary education in India. The three attendance track are also distinct in the type of educational content they impart and have distinct labor-market implications. Technical degree courses include professional degrees in fields like medicine, engineering and architecture as well as job-oriented degrees like Bachelors of Computer Application, Business Administration, Information-Technology (IT), Pharmacy or Hotel Management. These courses are offered both by government and private institutions and are regulated by the All-India Council for Technical Education (AICTE). General degree courses are non-technical and award a bachelors degree in either the arts, sciences or commerce, further categorized according to subject. Mostly, these are offered by the government via central or state level universities and colleges. Vocational courses are not academic and focus on imparting a set of skills (rather than broader academic knowledge) targeted towards employment in a specific sector. They are offered by both government and private institutes. Under the government, these courses are offered either by Industrial Training Institutes/Centers (ITI/ITC) or by Polytechnics.

Recent reports of the NSS 71st round on education expenses, estimates the average yearly costs for technical/professional degrees to be a little over 60,000 rupees (approx. 1,000 dollars) with the expenditure on private institutions being 1.5-2.5 times the cost of government institutes. Average yearly expenses for a general education, in contrast, were found to be around 10,000 rupees (approx. 150 dollars) and for vocational courses, around 30,000 rupees (approximately 450 dollars). Measured wage premiums for technical degrees are more than a 100% of the wages of those who complete high school. Despite the fact that vocational training is more expensive than general degree courses, wage premiums for vocational courses (42% of high-school wage) are around 8 percentage points lower than the wage premiums for general courses.

Another feature of higher education in India is that students study in a specific subject-stream during 11th and 12th grades. This is the case in the current sample and is also true nationally. Typically, there are three subject streams: (1) Arts/Humanities, (2) Commerce and (3) Science. As is discussed subsequently, students' current stream of study is expected to be strongly correlated with future post-secondary education choice on account of preferences, with regards to eligibility for specific courses or degrees within tracks and also, and also on account of ability (measured by test-scores) and socio-economic status (SES). In this paper, we discuss heterogeneity in the impact of the treatment, by students' current stream of study, because a-priori, we expect that students from different streams would have different baseline intentions of pursuing different tracks. In section 1.5.2, we further discuss

correlates of students current stream of study to frame our findings.

1.3 Conceptual Framework

I discuss here a simple model of belief updating proposed in Wiswall and Zafar (2015*b*) which is useful to frame the set-up, analysis and findings of this paper. The model highlights that students update beliefs about their own-earnings, upon receiving information about population earnings if (1) they are misinformed about populations earnings and (2) their beliefs about their own earnings are linked to their beliefs about population earnings. Additionally, the function that links population earnings beliefs to own earnings beliefs, known as the updating function, varies at the level of the individual, and matters in determining both the direction and extent to which individuals update beliefs.

Let X_{it} be individual $i's$ expectation at time t about her own earnings at some future date, denoted X and let Ω_{it} denote $i's$ information set at time t. Prior to receiving information, in the pre-stage, respondent i reports her beliefs about self earnings as:

$$X_{it} = E(X|\Omega_{it}) = \int X dG_i(X|\Omega_{it}) = f_i(\Omega_{it}) \tag{1.1}$$

where $G_i(X|\Omega_{it})$ is individual $i's$ belief about the distribution of future earnings conditional on the information Ω_{it}. $f_i(.)$ is the updating function that provides the

mapping between the individual's information set to beliefs about own-earnings at some future date.

An individual's information set has two parts: $\Omega_{it} = \{I_{it}, B_{it}\}$. Here, let I_{it} be individual $i's$ current belief about the information we provide in our treatment-average track-specific post-secondary education earnings in the Indian population. B_{it} contains all other elements of an individual's information set which includes both other population-level information and private information available only to the individual like her perceived ability to succeed in a particular track. After the provision of information, in the post-stage, the individual's information set is Ω_{it+1}. At this stage, we also elicit her beliefs about her own-earnings at a future X_{it+1}, again.

Two conditions are necessary for an individual to update their beliefs about their own earnings and for $X_{it} \neq X_{it+1}$:

1. $I_{it} \neq I_{it+1}$ and the individual should not already know the information that we provide. Therefore the information should be new and also accepted by the individual as credible.
2. $f_i(\Omega_{it}) \neq f_i(\Omega_{it+1})$ and the individual should consider the population-level information as relevant to themselves.

If we observe that individuals at baseline have beliefs about population earnings that are substantially different from the information we provide, then condition 1 is

met and the information provided is likely "new" to the individuals in the sample.

If individuals do not update own-earnings beliefs, despite the information being new, i.e. $\frac{\partial f_i(\Omega_{it+1})}{\partial I_{it}} = 0$, then the general rules stated above imply that the new information was not relevant to them. A more specific model of the process of belief updating discussed above is Bayesian updating, the benchmark model for analyzing belief updating, which imposes specific restrictions on the $f_i(.)$ function in Equation 1.1. In our case, a modification of Bayesian updating applies because individuals receive information over one variable (population earnings) and update beliefs regarding a separate variable (own earnings). In this Quasi-Bayesian case, updated earnings (X^B_{it+1}) are a linear combination of an individual's prior beliefs (X_{it}) and new information about population earnings (I_{it+1}), wherein the relative weight placed on the new information is the variance of the prior belief $V(X_{it})$ divided by the variance of the new information $V(I_{it+1})$, i.e. $\frac{V(X_{it})}{V(I_{it+1})}$. Therefore, a core prediction of the Bayesian model of updating is that individuals are more responsive to information regarding a quantity that they have weaker priors about (i.e. higher $V(X_{it})$) (DellaVigna and Gentzkow (2010)).

In this paper, we utilize the core prediction of the Bayesian model to rationalize differential updating between individuals with identical information sets. $V(I_{it+1})$ is the same for all individuals as the same track-specific information is provided to everyone, and therefore, variation in responsiveness to information stems from differences in the variance of prior beliefs. However, this evidence is suggestive because we do not directly measure individuals' variance of baseline priors and a body of literature

in economics and psychology documents deviations in individual updating compared to what the Bayesian model would predict (Kahneman and Tversky (1972); Wiswall and Zafar (2015*b*)). Therefore, while we cannot fully explain the nature of differential updating, we do establish that the direction and magnitude of baseline population errors cannot explain a significant portion of own-belief updating. In other words, the heterogeneity in individual-level updating is important. We show that this is the case by highlighting differential updating of own-earnings beliefs for sub-groups with statistically identical baseline-errors. The documented differential updating of own-earnings beliefs also has important consequence for the manner in which these sub-groups update enrollment probabilities and borrowing intentions- decisions that take updated own-earnings beliefs as inputs. This points to the limited potential for an information campaign to induce updating of individual beliefs despite accurate knowledge of information gaps in a particular population.

1.4 Data & Experiment Details

1.4.1 Data collection & Timing

The data for this study was collected from a sample of 1525 students across nine public schools in the East Indian state of Jharkhand. All nine schools are constituent units of a large state university and the students, at the time of the survey,

were studying in in their 12th grade.[4] Four of the nine schools are situated in the capital city of Ranchi, one in a rural block of Ranchi district and four others are in surrounding rural districts. The survey was conducted between October 2014 and February 2015, five-nine months prior to the time when students make actual decisions regarding enrollment in post-secondary education.

Figure 1.A.1 highlights the structure of the survey. Half of the complete sample was randomly assigned to the information treatment group and the other half to the control group. The sample was also stratified by gender and current stream of study to ensure equal representation of the two sets of groups across treatment and control (Duflo, Glennerster and Kremer (2007)). We drew, approximately, an equal number of students from each school. Further, within each school, students were randomly assigned to survey-sessions of 15 students each. Survey sessions were either a control session or a treatment session, with the latter differing only on account of the feature that it included an approximately 20 minute long information session, at the end of the collection of baseline data and disbursal of loan cards. For a given survey-session, round 2 of data collection was conducted the day after the first round.[5] In every school, both rounds of all control sessions were conducted before the

[4]Specifically, these students were studying in the final year of their "intermediate degree" in what are known as "intermediate colleges". After completing 10th grade, students chose between attending either an intermediate college, for two years of higher-secondary schooling, or attending a high school which offers 11th and 12th grades. Public intermediate colleges, like the ones surveyed here, are often co-located with public colleges offering undergraduate degrees. Since intermediate education is equivalent to higher secondary education, I refer to these students as being in 12th grade, throughout the paper, to avoid confusing terminology as most people think of colleges as referring to only post-secondary education.

[5]The short time-period between round 1 and round 2 of the survey follows from the research designs of Wiswall and Zafar (2015*a*) and Osman (2014). The short-time span between rounds allows one to be sure that all other factors in an individuals utility function that are correlated

treatment survey-sessions, in order to prevent students from the treatment group to share information with students in the control group, in a manner that can influence the results of this paper. Both sets of students answered exactly the same round 1 and round 2 questions. Survey sessions were conducted in classrooms within the students school and were led by a team of two enumerators. Students answered the questions, posed by the enumerators, on android tablets. The questionnaires were fielded using Open Data Kit (ODK) software.

1.4.2 Survey Questionnaire & Information Treatment

Round 1 of the survey consisted of questions on (i) socio-economic details including gender, caste, religion, a household assets module, parental education and occupation, older sibling gender and education, scores on previous centralized board examinations and history of grade repetition and (ii) baseline beliefs contingent on each higher education alternative i.e. technical/professional degrees, general degrees, vocational diplomas/certificate courses and the fourth alternative of not attending further education after 12th grade. While the three post-secondary education tracks were constructed to maintain consistency with education data collected by the country's National Sample Survey (NSS), the categories are broad and encompass a variety of courses of study. Therefore, data collection was preceded by a detailed explanation

with earnings beliefs remain invariant and also limits the time that students in the control group have to acquire information from other sources, over time. The drawback is that I cannot comment on the process of expectations formation over the long term or on the persistence of the effects of information provision. However, Wiswall and Zafar (2015*a*), who collect revised beliefs both instantaneously and over the long term, find the effects of information provision to be strongly persistent two years after the provision of information.

of possible courses/degrees that are part of every category. Since a majority of the beliefs questions were either probabilistic in nature or required students to express responses on a scale of 0-100, the baseline beliefs module was also preceded by a discussion (with examples) on answering probabilistic questions[6].

In the baseline beliefs module, stated probabilities of enrollment were elicited for (i) all four higher-education alternatives[7] and (ii) only for higher education alternatives that comprise an individual's affordable choice-set. Next, individuals were asked about certain non-pecuniary and pecuniary beliefs conditional on each education alternative. Pecuniary beliefs included data on expected probability of employment and expected average monthly earnings. These pecuniary beliefs were collected both for individuals perceptions regarding their own expected labor market outcomes and outcomes they believe apply to an average individual in the population[8]. Non-pecuniary beliefs included questions regarding enjoyment of coursework, parental

[6]We ensured that answers to all probabilistic questions sum to 100 by placing the total as a constraint in the questionnaire, without fulfilling which, the survey would not proceed to the subsequent question.

[7]The exact wording of the question used to elicit enrollment probabilities for potentially hypothetically choice sets of individuals was: *"Think ahead to next year when you have completed (sic) intermediate. Imagine that you have passed your (sic) intermediate examinations and are able to secure admission in one degree/course belonging to each of the options 1, 2 and 3. Option 4 is also available to you. Suppose that you are provided with financial aid such that all your expenses (tuition, boarding, room, etc.) are paid for at a private/government institute for a course belonging to each options 1, 2 and 3. State the percent chance that you would enroll in each of the following?"* This statement was followed by the four education options among which students had to allocate probabilities.

[8]For e.g. the question used to elicit own earnings beliefs was: *Consider the situation where you graduate from a degree belonging to the alternative insert track. Look ahead to when you will be 30 years old. Think about the types of jobs associated with degree/course. How much do you think YOU would earn per MONTH on AVERAGE, if you completed a degree of this type?* "You" was replaced with the phrasing "Typical person" to elicit beliefs about earnings of an average person in the population.

approval of education track and likelihood of graduation. In this paper, we are interested in disentangling the effect of information-gaps in one particular aspect of individuals' information sets- their knowledge about the distribution of population (public) earnings by post-secondary track. Therefore, the only belief our experiment manipulates (and which we collect post-treatment data on) are individuals' beliefs regarding track-specific expected average monthly earnings. We utilize beliefs about expected average monthly earnings in this paper, and the other aforementioned belief variables are not analyzed in detail here. Secondly, since the focus of this paper is on recovering the elasticity of enrollment intentions to earnings beliefs, we utilize data on all four higher education alternatives hypothetically "available" to an individual. Restricting estimation to only affordable alternatives biases our parameter of interest, as individuals constrained by costs might appear falsely unresponsive to the information intervention.

Another part of the data-collection focused on measuring the demand for higher-education loans in our sample. Therefore, additionally, at the end of round 1, all students were given a loan-card which had two questions related to borrowing for higher education which they had to think about at home and discuss with their family members. The two questions were- a) whether the individual would like to accept a loan, offered at a fair interest rate, for attending higher education, to be repaid only after completion of their studies- yes or no b) If yes, keeping in mind the length of their desired degree, how much would they like to borrow on a yearly basis?

The 20 minute information session discussed the average and the 25th and 75th percentile of the monthly earnings distribution of men and women who have completed each higher education alternative. This data was calculated from two latest rounds of National Sample Survey (NSS) data[9]. Individuals part of the information treatment group also took home a sheet of paper with a graph and some statistics that summarized the contents of the information session that they were part of. The script of the information-session is reproduced in section 1.A and the information sheet taken home by the students is given in Figure 1.A.2. The loan card taken home by the students is given in Figure 1.A.3, along with the accompanying loan script.

The next day, for round 2, students were (i) re-asked about their stated enrollment probabilities for all four higher education alternatives, (ii) expected average monthly earnings for each higher education alternative. In addition, their response to the questions posed in the loan card were also recorded.

1.5 Results

1.5.1 Covariate Balance

Table 1.B.1 in section 1.B summarizes the key background variables of sample individuals and checks for balance in these characteristics across control and treatment

[9]Refers to two latest rounds of employment-unemployment data; i.e. - NSS 66th round (2009-10) and NSS 68th round (2011-12)

groups, for the full sample. Control and treatment individuals do not differ statistically on account of almost all relevant socio-economic and demographic characteristics, at baseline. However, we see that control individuals are more likely to own land (p-value=0.04) and individuals in the treatment group have a slightly higher index of household assets (p-value=0.10). Nevertheless, one other variable that is also indicative of the individuals households well-being, namely the HH Facility Index, does not statistically differ between control and treatment groups. More importantly, baseline differences in land ownership and household assets, do not manifest in statistically different baseline enrollment probabilities. Figure 1.4-Figure 1.7 also show that there are no pre-existing differences between the two groups in the distributions of track-specific own-wage beliefs.

Table 1.B.2 breaks down the sample by current stream of study. Here, the Arts and the Science streams seem to be balanced on baseline variables, but there are some imbalances in the commerce stream (5 out of 20 variables). However, some of the variables go in opposite directions. For instance, treatment group individuals have a higher asset index but are less likely to own land. Therefore, in Table 1.B.3, I complement Table 1.B.1 & Table 1.B.2 by using the F-test approach to testing for balance. Here, for the commerce stream, the p-value for the F-test that all coefficients are zero is around 0.30.

1.5.2 Correlates of Current Stream of Study

Sub-group heterogeneity in this paper is examined by students' current stream of study, a dimension along which the survey sample was stratified. Typically, higher-secondary education in India (grades 11th and 12th) entails students to be enrolled in one of three streams of study- (1) Arts (humanities), (2) Commerce or (3) Science.[10] Students' current stream of study is strongly correlated with their future post-secondary education choices, in part because it often determines eligibility for future study. That is, which particular degrees/courses a student could potentially study within the three attendance tracks discussed in this paper, is to a large extent determined by their stream of study at the higher-secondary level. Accordingly, students' preferences for post-secondary study and eventual occupations are taken into account by them when they choose their stream of study in 11th grade. Hence, a-priori, the impact of track-specific information is expected to differ according to students' current educational stream. Students belonging to a particular stream take classes together and hence can also be expected to have correlated information sets at baseline and to further develop common proclivities towards type of future study.

Current stream of study is correlated with expected post-secondary enrollment. This can be seen in the last four rows of Table 1.B.4. Students in the Science stream are nearly 18 percentage points (pp.) more likely to want to enroll in technical tracks

[10]The arts stream includes subjects like history, political science, psychology, sociology, languages; the commerce stream includes the study of accounts, business, business mathematics and the science stream includes subjects such as physics, chemistry, computer science and mathematics. Economics can typically be studies across the three streams.

as compared to Arts students and 12 pp. more likely as compared to Commerce students. Arts and Commerce students are more likely than Science students to enroll in general tracks. Arts students state the highest non-attendance probabilities, followed by Commerce and then Science students.

For the sample under study the selection of stream in 11th grade was not purely based on preferences but followed a cut-off system where students apply to study in a given stream, and admission is based on points scored in the 10th grade board examination. The highest cut-offs were for Science, followed by Commerce and then Arts. Table 1.B.4 confirms that students in the Science stream scored, on average, nearly 11 pp. more than students in the Arts stream and roughly 6 pp. more than students in the Commerce stream, in the 10th grade. The Science group also has more males- almost 22 pp. more males than Arts and 16.5 pp. more males than Commerce. Other correlates are as expected. Students in the Science stream have the highest Asset/Household facility indices, are least likely to be lower caste (i.e. Scheduled Tribe), most likely to belong to the majority religion (Hinduism), and have the most educated parents and older siblings. These measures are least favorable to students in the Arts stream and Commerce students are in the middle.

1.5.3 Baseline Relationship Between Expected Earnings & Enrollment Intentions

The experiment in this paper follows from the premise that college enrollment decisions are based on *perceived* net benefits from college (Manski (1993)) and that subjective expectations of future earnings are important determinants of current education decisions (Arcidiacono, Hotz and Kang (2012);Wiswall and Zafar (2015*a*)). In Table 1.B.5 I provide *prima facie* evidence on the relationship between expected earnings and enrollment intentions, at baseline, in my sample. Here, I regress the probability of enrollment of individual i for track j, on individual and track-specific non-pecuniary and pecuniary beliefs. I control for individual (student) fixed effects and exploit only within-individual variation in beliefs and enrollment intentions, to estimate the importance of earnings as a determinant of intended enrollment. Nevertheless, these estimates are only suggestive and not causal because unobserved track-specific beliefs that are correlated with earnings beliefs, and predict intented enrollment, are not accounted for.

Consistent with previous literature (Delavande and Zafar (2014); Zafar (2013)) these estimates imply that expected earnings are small but statistically significant determinants of enrollment intentions and that non-pecuniary factors are generally more important in the decision-making process of students. The regression function underlying these results is linear-log in wages, therefore a 1% increase in wage beliefs regarding track j imply an increase of 0.023% increase in probability of enrolling in

track j (col. 1 of Table 1.B.5). Beliefs regarding expected enjoyment of coursework is the most important correlate of enrollment intentions (also the case in Zafar (2013)), with a 1% increase in the probability of enjoying coursework being associated with a 0.45% increase in the probability of enrolling in track j[11].

Additionally, it is relevant to note that the coefficient on "log own wage" is more than an order of magnitude smaller for Arts students as compared to the other two groups and statistically insignificant (col. 2 and 6 of Table 1.B.5). To the extent that it is costlier for individuals to process or pay attention to information not relevant to their decision-making process (Hanna, Mullainathan and Schwartzstein (2014);Sims (2003)), we might expect these students to not update their own-earnings beliefs in response to information provision. If the baseline elasticity of enrollment to earnings is strongly correlated with the experimental elasticity, we might expect these students to not update enrollment intentions/borrowing decisions despite updating own earnings beliefs.

1.5.4 Baseline Beliefs Regarding Population Earnings

Figure 1.1 plots the distribution of logged wage beliefs held by males and females in the sample, for an average person in the population. In Indian Rupee (U.S. Dollar)

[11] If I estimate this relationship using a log-odds specification, comparable to the reduced form model of Wiswall and Zafar (2015*a*) estimated with cross-sectional data, then my estimates imply that a 1% increase in beliefs about own-earnings in a track (relative to own-earnings for non-attendance) increase the log-odds of enrolling in that track by 0.2%. This estimate is much smaller than their estimated elasticity of 1.6%.

terms, the "true" (measured from nationally representative data) average monthly earnings for working age individuals having completed a technical education track is Rs. 22,071 (328 USD) per month for males and Rs. 16,453 (245 USD) per month for females. Average monthly earnings for having completed a general education track is Rs. 15,280 (227 USD) per month for males and Rs. 12,750 (190 USD) per month for females and average monthly for having completed a vocational education track is Rs. 14,495 (216 USD) per month for males and Rs. 12,210 (182 USD) per month for females. Average monthly earnings of those who don't pursue post-secondary is Rs. 9,973 (148 USD) per month for males and Rs. 8,907 (132 USD) per month for females. Thus, measured college premiums for completing post-secondary education are high and range from around 121 (85) percent for technical tracks to 45 (37) percent for vocational tracks, for males (females).

Figure 1.1 indicates that a majority of males seem to substantially over-estimate population wages for the three attendance tracks and for the non-attendance alternative. A majority of females also seem to over-estimate population wages[12]. However, for the three attendance tracks, the proportion of over-estimators is smaller for females as compared to males and for the non-attendance alternative the proportion of over-estimators is smaller as compared to the attendance tracks. In investigating the role of information gaps with regards to college attendance, we are interested in the errors that individuals make for the attendance tracks, relative to the non-attendance

[12]Interestingly, Bonilla, Bottan and Ham (2016) and Gamboa and Rodríguez Lesmes (2014) also find that their respective samples of high school students substantially overestimate the wages of college graduates in Colombia. Therefore, even within low-income populations, among the demographic of high school students, underestimation of college earnings does not seem to be a serious impediment to individuals under-investing in college-level education.

alternative. In this regard, males can be said to have more accurate beliefs at baseline as compared to females. Table 1.1 tabulates the percentage of students who over-estimate earnings in all four tracks. The "Full Sample" panel of Table 1.1 indicates that 70% of males overestimate population earnings for the non-attendance alternative. This proportion is higher by 2, 4 and 13 percentage points for technical, general and vocational tracks, respectively. In contrast, 49% of females overestimate population earnings for the non-attendance alternative. For girls, this proportion is higher by 21, 13 and 17 percentage points for technical, general and vocational tracks, respectively.

Figure 1.2 plots the distribution of logged wage beliefs, for an average person in the population, broken down by students' current stream of study. Three facts are apparent in these figures. One, for all tracks, the extent of over-estimation is higher for students in the Commerce and Science streams, as compared to students in the Arts (Humanities) stream; two, the distributions of population-beliefs for Commerce and Science students closely overlay each other; three at least for students in the Commerce & Science streams, the extent of over-estimation is higher for the three attendance tracks as compared to the non-attendance alternative. Stream-specific panels in Table 1.1 further illustrate these points. While for students in the Arts stream there is no dominant direction in which baseline errors prevail (especially when attendance tracks are compared to the non-attendance alternative), for Commerce and Science students a majority of students (1) overestimate earnings for all tracks and (2) overestimate attendance earnings to a larger extent than non-attendance earn-

ings. In addition, for both of these streams, a much larger proportion of females, as compared to males, over-estimate attendance earnings relative to the proportion that over-estimates non-attendance earnings.

Figure 1.3 gives an idea of the relative magnitude of overestimation versus underestimation in the sample. It is a scatter plot of the percentile mean of baseline population errors where "error" is defined as (perceived population wages)$_{ij}$-(true population wages)$_{ij}$ for individual i and track j, and measured in true-wage units. Looking at errors on either side of the zero-error line, and with added focus on errors within 1 true-wage unit of zero-error, we see that for the three attendance tracks there are substantially more individuals one-unit above the true wage than there are below, though, within this range, individuals are more evenly distributed for the non-attendance track.

1.5.5 Impact on Own-Wage Beliefs

The impact of the treatment on own-wage beliefs is measured first for each track separately (Equation 1.2) and then for each attendance track relative to non-attendance (Equation 1.3):

$$log(W_{ijt}) = \alpha + \beta_1 Post + \beta_2 T + \beta_3 (Post \times T) + \theta X_{it=1} + u_{ijt} \tag{1.2}$$

$$log(W_{ijt}) - log(W_{iJt}) = \alpha + \beta_1 Post + \beta_2 T + \beta_3 (Post \times T) + \theta X_{it=1} + u_{ijt} \quad (1.3)$$

Where $log(W_{ijt})$ is the log of own-wage belief of individual i, conditional on enrollment in track j, at either $t = 1$ (pre-treatment) or $t = 2$ (post-treatment). $Post$ is a dummy variable which equals 1 for post-treatment data, T is a dummy variable which equals 1 for individuals in the treatment group. β_3, our coefficient of interest, measures the average effect of the treatment on updating of own-wage beliefs. $X_{it=1}$ denotes baseline controls and u_{ijt} is a mean zero error term. $log(W_{iJt})$ is the log of own-wage beliefs of individual i for the non-attendance track.

The latter specification is important because we analyze enrollment decisions in a log-odds framework and interpret attendance log-odds relative to a base-case of non-attendance.

1.5.5.1 Full Sample

Figure 1.4-Figure 1.7 plot pre and post treatment distributions of own-wage beliefs for control and treatment groups, by track. To focus on the bulk of the distribution and to avoid stretching out the densities to the extremes, I plot densities in the 1-99 percentile range of the data. The presented Kolmogorov-Smirnov p-values for equality of distributions are however based on the full data. For all four tracks,

there are no baseline differences in the respective distributions. Post-treatment, the distribution for the three attendance tracks shifts leftward (a downward revision) and this shift is statistically significant. The shift is perceptibly larger for general and vocational tracks. There is no statistically discernible shift in the distribution of non-attendance earnings.

Table 1.2 examines the effect of the information treatment on updating of own-wage beliefs in a regression. Panel A looks at each track separately and Panel B presents updating for each of the three attendance tracks relative to updating for the non-attendance alternative. For all four tracks, the treatment is associated with a downward revision in own-wage beliefs, but the revision is statistically significant for only one track (vocational). Relative to non-attendance, the overall effect of the treatment on updating of attendance-track wage beliefs for all three tracks is not statistically significant. The effect-sizes imply an upward revision of earnings-beliefs of around 6% (technical track) and downward revisions ranging from around 3 to 7.3 percent (general and vocational tracks).

1.5.5.2 By Baseline Error

Table 1.3 examines the effect of the treatment on own wage-belief updating, separately for those who under and over estimate track-specific population wage beliefs at baseline[13]. Panels A and C look at updating for all four tracks separately, for under

[13]Baseline under estimators are those for whom (perceived population wages)$_{ij}$-(true population wages)$_{ij} < 0$. Over-estimators are conversely defined.

and over-estimators, respectively. Panels B and D present updating relative to the non-attendance track. In this case baseline under (over) estimators are also defined as those who under (over) estimate attendance-track population earnings relative to non-attendance[14].

Focusing on Panels A and C, in general, under-estimators seem to revise wage beliefs upwards and over-estimators seem to revise wage beliefs downwards (3 out of 4 tracks in each case). Wage beliefs revisions for baseline under-estimators are relatively smaller and statistically indistinguishable from zero as compared to wage belief revisions for over-estimators. This can partly be explained by differences in the extent of baseline errors between the two-groups, shown in Figure 1.3. Overall, there are fewer under-estimators than over-estimators (20-30% of the full sample, depending on track), and over-estimators are farther away from the zero error line than are under-estimators. This is true, even if we restrict our attention to 1 true-wage unit below and above zero. Among over-estimators, individuals revise wage-beliefs downwards for all four tracks, with the magnitudes being largest (and statistically significant) for the general and vocational tracks. However, the magnitude of downward revision for the non-attendance track is also quite large. As can be seen in Panel D it is not possible to reject the hypothesis that wage-revisions, relative to non-attendance, on account of the treatment are zero. The same holds for baseline under-estimators in Panel B.

[14]Therefore, for this specification, baseline under estimators are those for whom $\{[(\text{perceived population wages})_{ij}\text{-}(\text{true population wages})_{ij}]\text{-}[(\text{perceived population wages})_{iJ}\text{-}(\text{true population wages})_{iJ}]\} < 0$

1.5.5.3 By Current Stream of Study

Table 1.4 examines the effect of the treatment on own wage-belief updating, by students' current stream of study, an important determinant of post-secondary education decisions. For each of the three streams- Arts/Humanities, Commerce and Science I first examine updating for all four tracks (Panels A, C, and E) and then updating for the three attendance tracks relative to non-attendance (Panels B, D, and F). For students in the Arts stream, the impact of the information treatment on own wage revisions is statistically insignificant. Individuals revise own-wage beliefs downwards by similar magnitudes for general, vocational and non-attendance tracks, implying small (1.5-2.2 percent) downward revisions for general and vocational tracks relative to non-attendance.

In contrast, wage belief updating for attendance tracks relative to the non-attendance alternative (Panels D & F), are large and statistically significant for Commerce and Science students, but run in opposite directions. Students in the Commerce stream, strongly revise own-wage beliefs downward for all three attendance tracks, relative to the non-attendance alternative (Panel D). Here, the magnitudes of wage belief updating indicate downward revisions of the magnitude 20-30 percent in treatment relative to control groups[15]. This is driven by large downward revisions for the attendance tracks (specifically general and vocational tracks) and no statistically discernible (but upward) updating for the non-attendance track (Panel C).

[15] I use the formula prescribed in Kennedy et al. (1981) to interpret interaction terms as the estimating equation is of log-linear form and the independent variables for interest are dummy variables.

For the third group of students, students in the Science stream, the treatment induces them to revise relative attendance earnings upward for all three tracks (the effect is statistically significant for technical and general tracks). This is driven entirely by a strong downward revision in wage-beliefs for the non-attendance alternative and no systematic updating for the three attendance tracks looked at separately (Panel E).

I also find that the pattern of relative wage belief updating established in Table 1.4 is largely driven by females in the sample. A part of the explanation for this could be that females, as compared to males, perceive the returns to attendance, relative to non-attendance, more inaccurately. This is shown in Table 1.5. Downward revision is much stronger for females in the Commerce stream (the differential ranges from 24 to 33 percent) and the upward revision in the Science stream is driven entirely by females (Panel C). Females in the Science stream revise own-wage beliefs upwards by magnitudes of 43-66 percent in treatment relative to control groups. Table 1.6 confirms that this pattern holds even if we restrict the sample for these two streams to only baseline over-estimators. Therefore, differential updating between Commerce & Science groups exists holding fixed the direction of baseline error.

Differential updating by Commerce and Science students is further apparent in Table 1.7 where we pool the three attendance tracks and examine own-wage revision as a function of the magnitude of baseline error[16]. A statistically significant "treat-

[16]The regression specification here is:

$$(W_{ijt=2} - W_{ijt=1})^T = \alpha + \beta_1 error^T + \beta_2 T + \beta_3 (error^T \times T) + \theta X_{it=1} + u_{ijt} \tag{1.4}$$

Here, the dependent variable, W^T_{ijt} which measures own-wage revision and "$error^T$" which mea-

ment x error" coefficient implies that own-wage revisions are a systematic function of baseline error. A negative coefficient on the interaction term implies that larger amounts of baseline under-estimation are associated with larger upward revisions in treatment relative to control group. Focusing on columns (4)-(6), which include the full set the baseline controls, we see that Commerce students systematically respond to information presented for the attendance-tracks and Science students respond to information presented for the non-attendance alternative.

Track by stream regressions in which wage-revisions cannot be systematically established as a consequence of the treatment indicate that the track-specific information provided was not relevant to the individuals of a given stream. In section 1.6, I discuss that differences in updating between Commerce and Science students is not a mechanical consequence of sub-group differences in baseline errors. I also provide some evidence that non-updating is consistent with the Bayesian model but cannot rule out the extent to which non-Bayesian updating constitute these findings.

1.5.6 Impact on Enrollment Intentions

Next, I examine whether updating of own-wage beliefs in response to information on public earnings leads to updating of track-specific enrollment intentions among the sample of students. I examine the impact of the treatment on enrollment in a

sures the difference between perceived and true population wage beliefs, can both take on negative or positive values. Therefore, both variables are transformed using an inverse hyperbolic since transformation, which behaves and is interpreted like a log-transformation, but allows keeping zero and negative values Bellemare, Barrett and Just (2013).

multinomial logit framework, elaborated in Equation 1.5.

$$\eta_{ijt} = log(\frac{\pi_{ijt}}{\pi_{iJt}}) = \alpha + \beta_1 Post + \beta_2 T + \beta_3 Track + \beta_4(Post \times T)$$
$$+\beta_5(T \times Track) + \beta_6(Post \times Track) + \beta_6(Post \times T \times Track) + \theta X_{it=1} + u_{ijt} \tag{1.5}$$

Here, $log(\pi_{ijt})$ is the stated probability at round t of individual i enrolling in track j and $log(\pi_{iJt})$ is the stated probability of non-attendance. η_{ijt} denotes the odds of choosing in track j as opposed to non-attendance. β_4 and β_6 are coefficients of interest, where β_4 measures the average effect of the treatment on the log-odds that an individual chooses the technical track as opposed to non-attendance and β_6 measures the differential log-odds (relative to the base track technical) of choosing general and vocational tracks.

Based on the log-odds regression in (1.5), the probability of enrolling in each track j is given by:

$$\Pi_{ijt} = \frac{\exp\{\eta_{ijt}\}}{\sum_{j=1}^{J} \exp\{\eta_{ijt}\}} \tag{1.6}$$

I use Equation 2.6 to compute the predicted probability of enrollment in each track for control and treatment groups in rounds 1 and 2. The marginal effect of the

treatment on the predicted probability of enrollment in each track is given by the difference $\{\hat{\Pi}_{jt=2} - \hat{\Pi}_{jt=1}\}_T - \{\hat{\Pi}_{jt=2} - \hat{\Pi}_{jt=1}\}_C$. Where the subscripts T and C are for treatment and control groups, respectively. $\hat{\Pi}_{jt}$ denotes the predicted probability of enrollment in track j, calculated using parameter estimates from (1.5).

This allows me to track how students allocate probability of enrollment across tracks at baseline and post-treatment.

1.5.6.1 Full Sample

Table 1.8 (Panel A) presents the effect of the treatment on the log-odds of pursuing each of the three attendance tracks relative to the base-case of non-attendance. However, we are interested not only in the relative likelihood of enrolling in each track relative to non-enrollment, but in the absolute probability of choosing each track which depends on how the three separate relative effects balance out each other. Therefore, in Table 1.8 (Panel B), I present the marginal effect of the treatment on the absolute probability of choosing each track. Together, both tables establish that the overall effect of the treatment on enrollment is small and statistically insignificant. This is consistent with the small effect of the treatment on the updating of wage beliefs for the full sample. This result does not importantly change when the sample is broken down by gender or by baseline error.[17]

[17] These result are omitted for brevity but available upon request

1.5.6.2 By Current Stream of Study

In Table 1.9 (Panel A), I examine the effect of the treatment on the log-odds of pursuing each of the three attendance tracks relative to the base-case of non-attendance, by current stream of study. In Table 1.10, I present these log-odds separately for males and females.

For students in Arts/Humanities, the effect of the treatment on enrollment log-odds is small, and statistically insignificant and the marginal effect of the treatment on the predicted probability of enrollment is also small Table 1.9 (Panel B). As can be seen in Table 1.10, for both males and females in this stream, we cannot reject the null that the effect of the treatment on enrollment log-odds, relative to non-enrollment, for each track is zero. This is consistent with the impact of the treatment on own-wage belief updating for these students.

For students belonging to the Commerce stream, there is a decrease in enrollment log-odds relative to non-attendance for technical and general streams (Table 1.9 (Panel A)), and this effect is entirely driven by females (compare panel B to A of Table 1.10), for whom there is a decrease in enrollment log-odds for all three attendance tracks relative to non-attendance. This is consistent with the fact that for this group of students, the overall effect of the treatment was a downward revision in own-wage beliefs for each of the three attendance tracks, relative to non-attendance. As can be seen in Table Table 1.9 (Panel B), which takes into account the relative size of track-specific treatment effects from Table 1.9 (Panel A), for Commerce students,

there is a decrease the probability of enrollment in technical tracks by around 4.7 pp. and increase probability of enrollment in general tracks (1.45 pp.), vocational tracks (2.77 pp.) and for non-attendance (0.477 pp.).

For students belonging to the Science stream, there is an increase in enrollment log-odds relative to non-enrollment for all three attendance tracks Table 1.9 (Panel A). A comparison of panel B to panel A in Table 1.10 shows that this effect of the treatment on enrollment log-odds is driven by females. This too is consistent with the fact that for this group of students, the overall effect of the treatment was an upward revision in own-wage beliefs for each of the three attendance tracks, relative to non-attendance. As can be seen in Table 1.9 (Panel B), for Science students there is an increase the probability of enrollment in technical tracks by around 3.45 pp. and decrease probability of enrollment in general tracks (0.505 pp.), vocational tracks (2.28 pp.) and for non-attendance (0.668 pp.).

For both Science and Commerce students, and specifically for females, the direction of updating of enrollment intentions for each attendance track relative to non-attendance, is broadly consistent with the direction of updating of wage beliefs for each attendance track relative to non-attendance. However, the overall effect of the treatment for Commerce students is to induce a movement away from technical tracks and towards other tracks (more so vocational tracks) and on the contrary the effect of the treatment for Science students is to induce a movement towards technical tracks and away from other tracks (more so vocational tracks). This fact cannot be explained by the difference in magnitude of wage-belief revision between atten-

dance tracks, which do not statistically differ from each other, within the groups of Commerce and Science students[18].

1.5.7 Impact on Borrowing

Recall that borrowing intentions for higher education were measured only post-treatment. Also, unlike stated enrollment intentions, the intent to borrow was not elicited as a track-specific decision. The average impact of the information treatment on borrowing intentions is given by β_1 in Equation 1.7 below:

$$Y_{it=2} = \alpha + \beta_1 T + \theta X_{it=1} + u_{it} \tag{1.7}$$

Where Y is a binary variable measuring whether or not the individual would like to accept a loan offer towards higher education enrollment. We may be concerned that the answer to this survey question might not be reflective of what would happen if a loan were actually made available, because individuals might not fully internalize the costs of borrowing while answering this question. While it is not possible to fully allay such concerns in this setting, it should be noted that the control group mean of the fraction of individuals wanting to borrow is only around 56 percent. This is despite the fact that on average only 1.04 tracks (out of 3) are thought to

[18] I refer here to panels D & F of Table 1.4. In a variant of these regressions, when tracks are included as an interaction term, I confirm that the magnitude of wage-belief updating for each attendance track does not statistically differ from the magnitude of updating for the other two tracks.

be affordable by individuals. The number of tracks affordable to individuals who do not want to borrow is 1 and this number is 1.08 tracks for individuals who do want to borrow.

Table 1.11 presents results on the impact of the information treatment on borrowing intentions, which was the only other primary outcome that we measured in our survey. Overall, treated individuals state a higher probability of intent to borrow, which is higher by 6.7 pp. By stream, this effect is largest and statistically significant only for students in the Science stream who have roughly a 15 pp. higher probability of wanting to borrow when compared with students in the control group. This represents a 25 percent increase in demand for borrowing, relative to the control group mean. This result is further consistent with an upward revision for this group of students in wage beliefs for attendance tracks relative to non-attendance. Conditional on loan acceptance, the amount of that individuals would like to borrow does not statistically differ on account of the treatment.

1.6 Can Heterogeneity in Updating be Explained?

In this section I discuss that while the wage belief updating of Arts students vis-a-vis the other two streams can be attributable to two observed patterns in the data, the differential updating between Science & Commerce students remains unexplained. This points to the existence of substantial heterogeneity in updating heuristics in the sample.

In section 1.5.3, and with reference to Table 1.B.5, we already established that ex-ante, we might expect Arts students to be less responsive to the information treatment and that is indeed what we find. This ex-ante prediction is based on the finding that for these students, at baseline, the enrollment elasticity of earnings beliefs is close to zero and statistically insignificant. Therefore, to the extent that it is costlier for individuals to process or pay attention to information not relevant to their decision-making process, we might expect these students to not update their own-earnings beliefs in response to information provision. Across tracks, the updating of own wage beliefs for Arts students, on account of the treatment, is statistically insignificant and we cannot reject the null that it is zero (first two panels of Table 1.3). The same analysis indicates that earnings beliefs seem to be important predictors of enrollment intentions for both Commerce & Science students, and the coefficient on log wages for both streams is of roughly equal magnitude. Experimentally, these students update relative own-earnings and also enrollment and borrowing intentions, in a manner consistent with the updating of own-wage beliefs. Therefore differences in the baseline relevance of earnings provide us with one explanation for why we may see differential updating for Arts as compared to Commerce & Science students. It cannot explain why the two sets of students, Commerce & Science, respond to different pieces of information and hence update relative earnings in opposite directions.

Therefore, next I examine whether differential updating can be rationalized on account of differences in baseline errors, regarding population earnings, between subgroups.

In Figure 1.2 we had established that the distributions of population wage beliefs for Commerce and Science students closely overlay each other. On the other hand, on average, Arts students seem to make smaller errors for all four tracks. This is further evident in Table 1.C.6. Here, we look at differences in baseline errors[19] between the three sub-groups in a regression framework, using OLS (col. 1) and quantile regressions (col. 2-6). Focusing our attention on col.1, it is evident that for all tracks, for students in the Arts stream, mean error is statistically significantly smaller (closer to zero error) than for students in the Science stream. However, the mean error for Commerce students does not statistically differ from that of Science students, for any track. Quantile regression results (col. 2-6) also consistently point to the fact that for several points along the distribution of baseline errors, Arts students differ consistently in their perceptions about population earnings when compared to Science students, while Commerce students do not. Therefore, while we cannot rule out the possibility that Arts students update own-earnings differently than students from the other two streams on an additional account of initial differences in perceptions regarding population earnings, this cannot explain differential updating between Commerce & Science streams. Therefore, it is evident that a substantial amount of updating heterogeneity in the sample is, most likely, not a mechanical consequence of differences in baseline errors regarding population earnings.

Next, I test whether the differential updating between Commerce & Science students can be explained by a core prediction of the Bayesian model. That is, I test whether individuals in the sample are more responsive to information regarding a track that

[19]Measured, as described in footnote 14, using an inverse hyperbolic sine transformation.

they are less likely to enroll in (DellaVigna and Gentzkow (2010); Oreopoulos and Dunn (2013)), and hence have weaker priors about. In Table 1.C.7, I establish that Commerce students have higher baseline likelihoods of non-attendance. This is the case both when all four tracks are in an individual's choice set, regardless of affordability (unconstrained choice set), and when only affordable tracks enter an individual's choice set (constrained choice set)[20]. In the unconstrained case, Commerce students state 1.4-2 pp. higher likelihoods of non-attendance compared to the reference category of Science students (who state about a 5.3% likelihood of non-attendance). It is apparent that when the cost constraint is removed and all tracks are hypothetically made available to all individuals, students state generally small probabilities of non-attendance. With regards to data on individuals constrained choice sets, wherein unaffordable options are assigned zero probability of attendance, Commerce students are about 6.6-9.2 pp. more likely to not-attend compared to Science students whose probability of non-attendance is about 50%.

In Table 1.C.8 I test whether individuals with a higher baseline probability of enrolling in a track are less likely to update earnings beliefs in response to the information treatment. I regress the absolute value of wage belief revision on levels and an interaction of the treatment dummy with the baseline probability of enrollment. While the effect of the treatment does not vary with the baseline probability of enrollment for the unconstrained case, the "treatment x baseline enrollment probability" interaction term is negative and significant (at the 5% level) when affordability of tracks is taken into account. Therefore, the fact that Commerce students are less

[20]In this case tracks unaffordable to an individual are assigned a zero probability of attendance.

likely to attend and more responsive to information on attendance tracks and Science students are more likely to attendance and less responsive to information on attendance tracks, is consistent with the core prediction of Bayesian updating bearing out in the data. Previous work in the literature leads us to believe that a portion of non-updating may also be non-Bayesian in nature (i.e. not explained by the variance of priors), but unfortunately in the absence of further data, I cannot comment on the extent to which that may be the case in this sample.

1.7 Conclusion

In this paper I present results from an information experiment, which randomized information on population earnings, for three post-secondary education tracks- technical, general, vocational and the final alternative of not pursuing post-secondary education. The experiment was carried out with 1525 12th grade students, across nine affiliated schools of a large, non-selective public state university in the Indian state of Jharkhand.

The impact of information provision is measured by students updating of own wage beliefs contingent on pursuing each post-secondary track, their stated probability of enrollment across tracks and borrowing intentions for higher education enrollment. Average impact of the treatment on the updating of own-wage beliefs and subsequent changes in enrollment intentions is small, though the impact on borrowing intentions is positive and statistically important. Average results mask considerable sub-group

heterogeneity, defined by the current subject stream of students. For two out of three sub-groups of students, the impact of the treatment on relative own-earnings beliefs, is statistically important. For these two sub-groups, own-wage belief updating is stronger for females, a pattern which may partly be on account of the fact that females perceive relative returns to attendance more inaccurately than males, at baseline. However, I also find that females are more responsive to the information treatment controlling for the size of baseline error (result omitted for brevity). Interestingly, Wiswall and Zafar (2015*b*) also find this to be the case in their sample of New York University (NYU) students. Within sub-group, the odds of enrollment, relative to non-enrollment, is consistent with direction of wage belief updating and is, reassuringly, stronger for the group (females) with larger wage belief updating. The effect of the treatment on borrowing intentions is also in line it's effect on wage-belief updating.

For the two sub-groups (Commerce & Science) for whom the impact of the treatment on wage beliefs for attendance tracks, relative to non-attendance, is statistically important, the updating takes place in opposite directions. This pattern is on account of the fact that individuals in the groups systematically respond to different pieces of track-specific information. Students in the Commerce sub-group revise wage beliefs downwards for attendance tracks only, and this pattern carries over to a downward revision in earnings beliefs for attendance tracks, relative to non-attendance. Science students revise wage beliefs downwards for the non-attendance track only, which translates into attendance earnings being relatively more attractive for this group,

post-treatment.

A combination of factors may explain why we see the first sub-group, students in the Arts stream, not revise wage beliefs in response to the treatment. Ex-ante, these students have a low elasticity of enrollment to wage beliefs and at baseline they make smaller errors, on average, with regards to beliefs about population earnings. However, these factors do not explain differential updating on the part of Science & Commerce students. Ex-ante, these students have a statistically important and similar in magnitude elasticity of enrollment to wage beliefs- therefore earnings likely play an important role in their decisions for future education. These students also make nearly identical errors with regards to population wage beliefs at baseline.

As discussed in the conceptual framework section of the paper, non-updating in response to "new" information implies that the piece of information provided was not relevant to individuals. Differential relevance of track-specific information to different sub-groups of individuals in the sample drives the heterogeneous impacts of information provision on own-wage belief updating. Sub-groups of individuals with equally biased information sets vary in their response to information significantly, depending on the extent to which their beliefs about population earnings are linked to their beliefs about their own. Track-specific non-updating can be Bayesian or "rational" or Non-Bayesian. Suggestive evidence implies that variation in updating may be attributable to the variance of individuals' priors (consistent with Bayesian updating), but without further data on individual-level distributions of own-wage beliefs, we cannot quantify the extent to which non-updating is Bayesian. However,

recent evidence (Wiswall and Zafar (2015*b*)) establishes that individuals do indeed deviate significantly from the Bayesian benchmark.

Recent papers in the literature which find information provision to have small average impacts on outcomes like test-scores or enrollment decisions state the presence of other binding constraints like credit constraints or lack of knowledge of the education production function as explanations. This paper offers another explanation for why the provision of population-level information on returns may lead to highly heterogeneous outcomes, by examining in detail the first-link in the causal chain that links population-level information to education outcomes, which is, the extent to which individuals update own-earnings beliefs in response to receiving information about population-level averages.

My study is a framed field experiment wherein participants deal with a subject of interest outside the experiment (their own education) but not in an environment where they would naturally undertake the task of thinking about their long term plans. Stakes for the participants were also low with no costs to paying less attention to the information provided. Therefore, the study was not designed to provide a model for scaling information provision at a national level, but to examine in more detail mechanisms (updating of beliefs and intentions) critical to the success of information interventions. For a policy-maker looking to implement an information campaign to induce more optimal education decision making, these findings imply, all else constant, a limited potential for an information campaign to induce, on average, updating of beliefs regarding oneself, of a particular magnitude and in a given

direction, despite accurate knowledge of information gaps in a particular population.

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Figures & Tables for Chapter 1

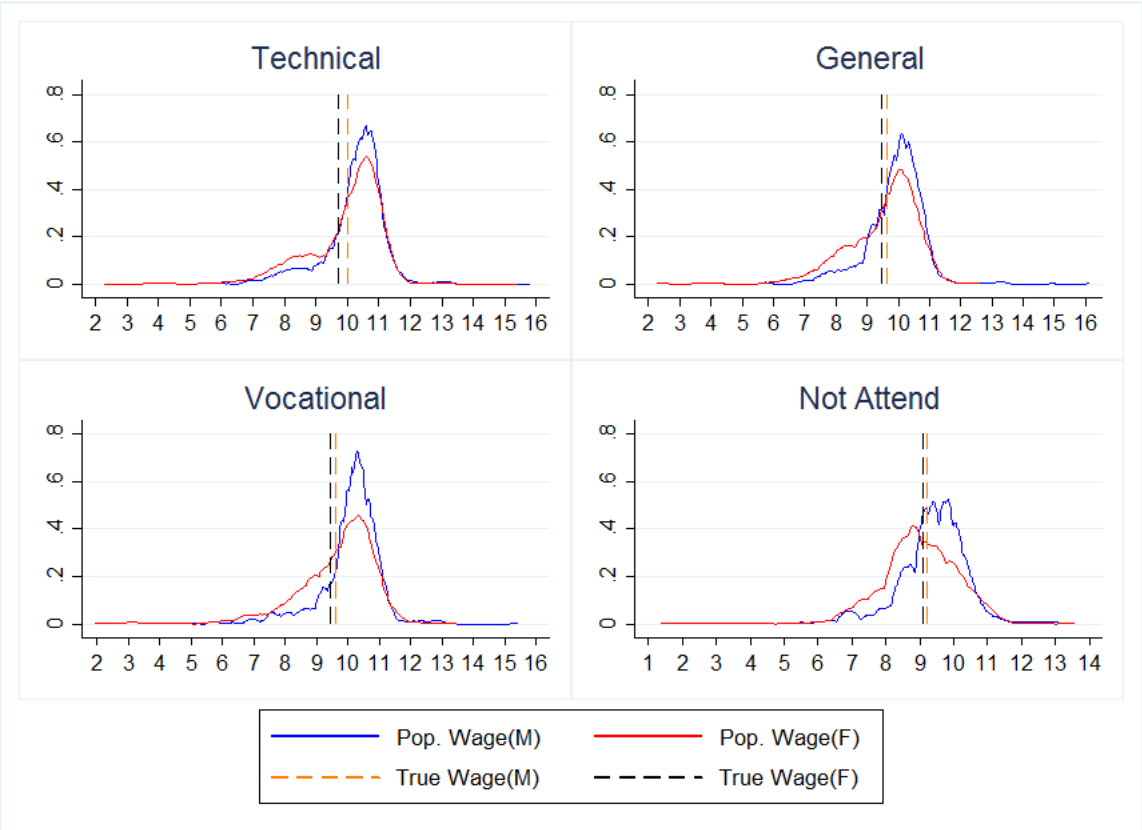


Figure 1.1: Log Population Wage Beliefs by Gender

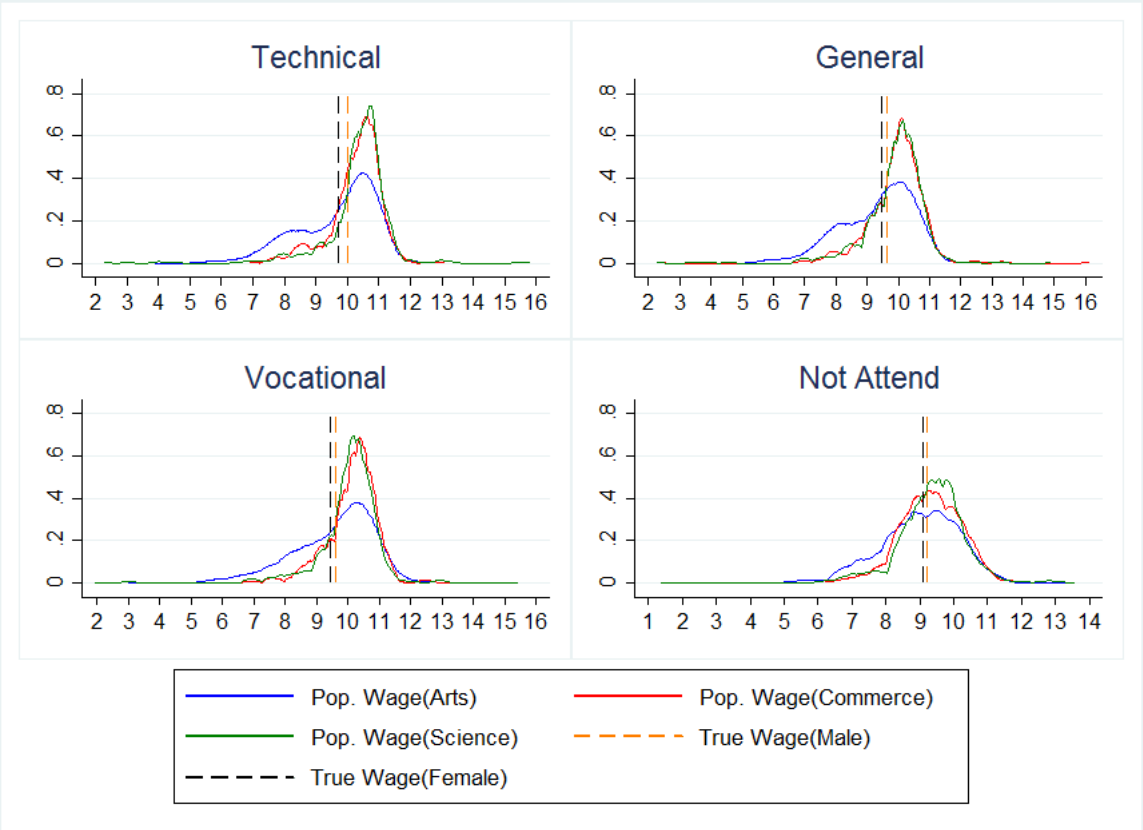


Figure 1.2: Log Population Wage Beliefs by Current Stream of Study

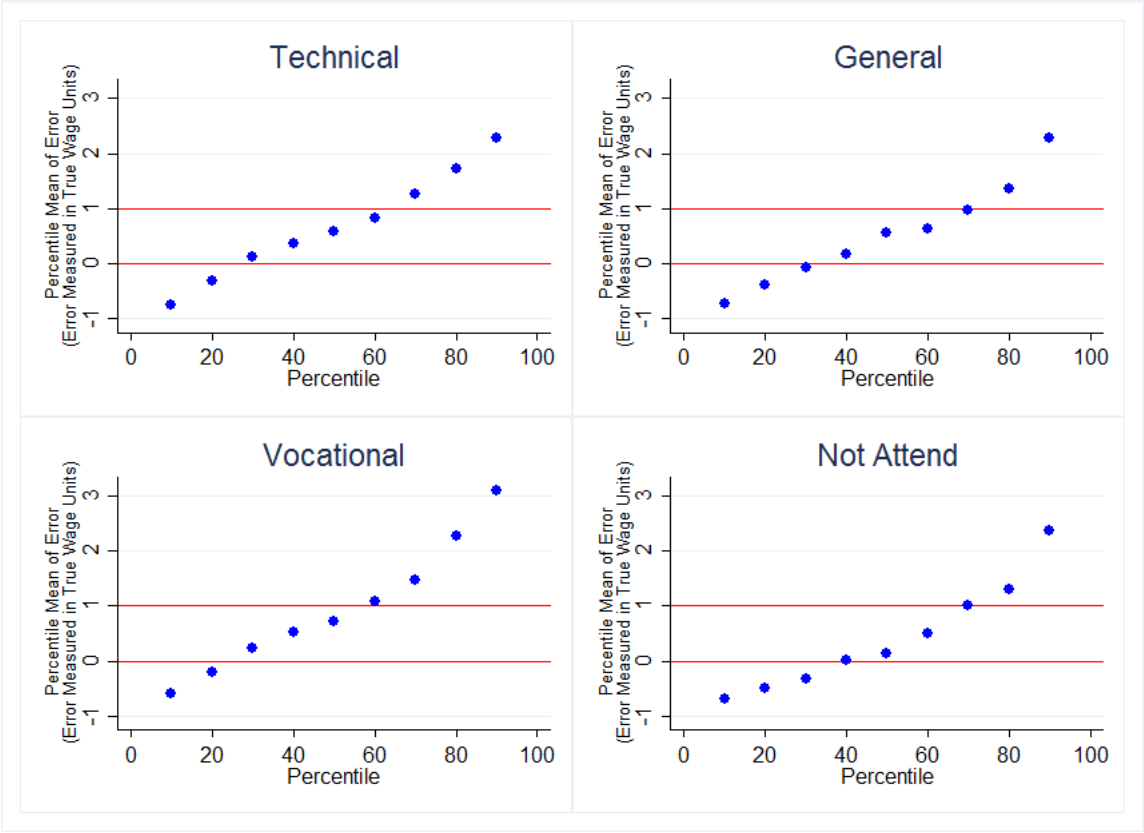


Figure 1.3: Scatter Plot of Baseline Population Errors Relative to True Wage (Zero-Error Line)

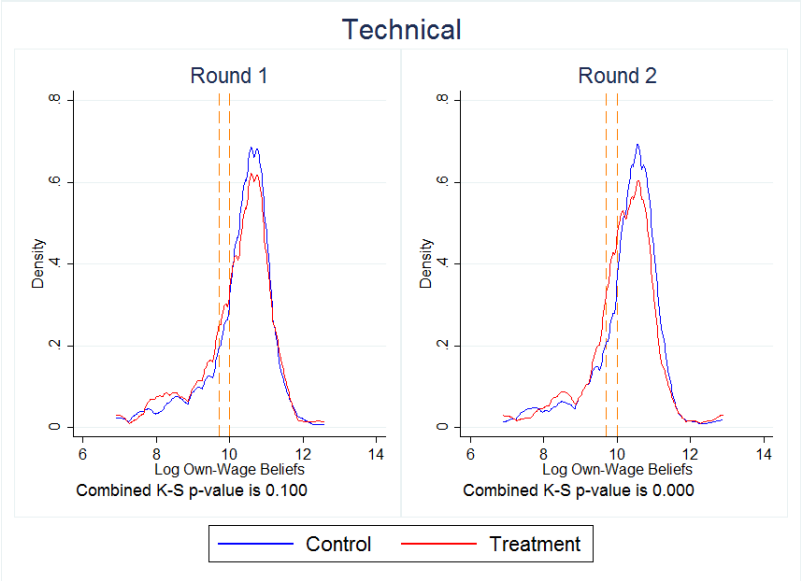


Figure 1.4: Pre and Post Distributions of Own Wage Beliefs for Technical Track; Range 1-99 Percentile

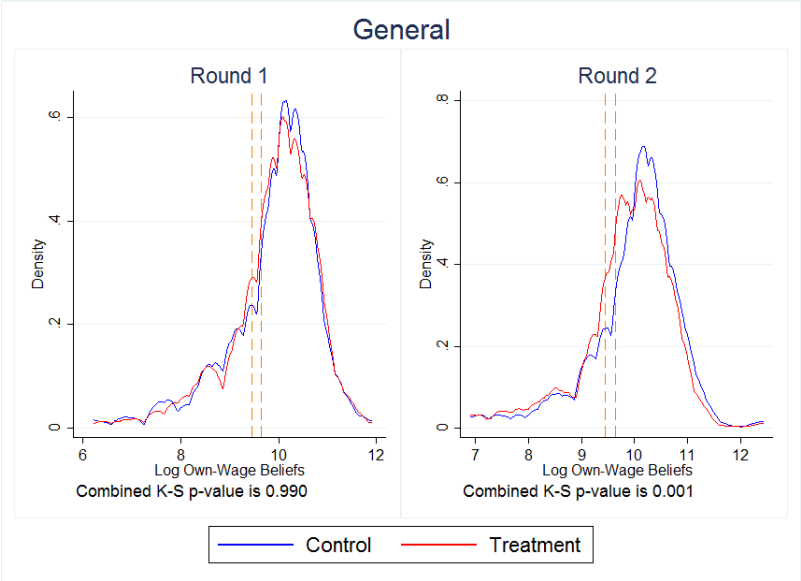


Figure 1.5: Pre and Post Distributions of Own Wage Beliefs for General Track; Range 1-99 Percentile

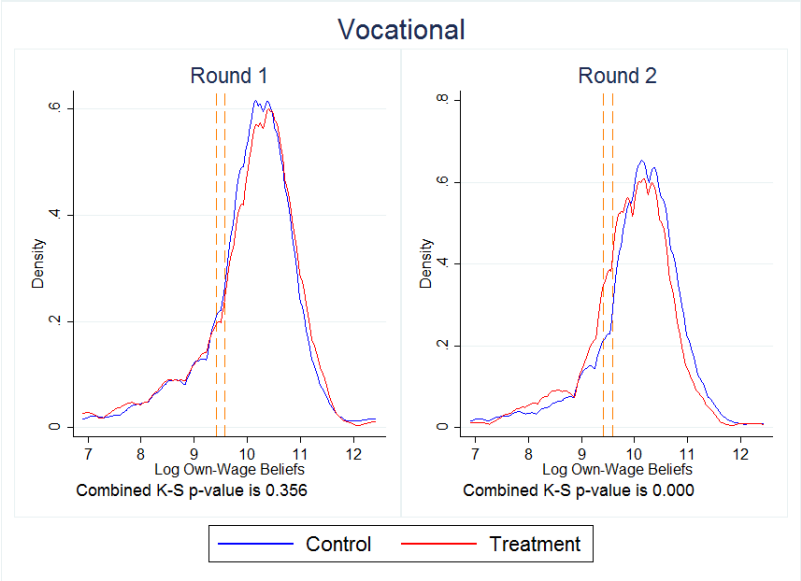


Figure 1.6: Pre and Post Distributions of Own Wage Beliefs for Vocational Track; Range 1-99 Percentile

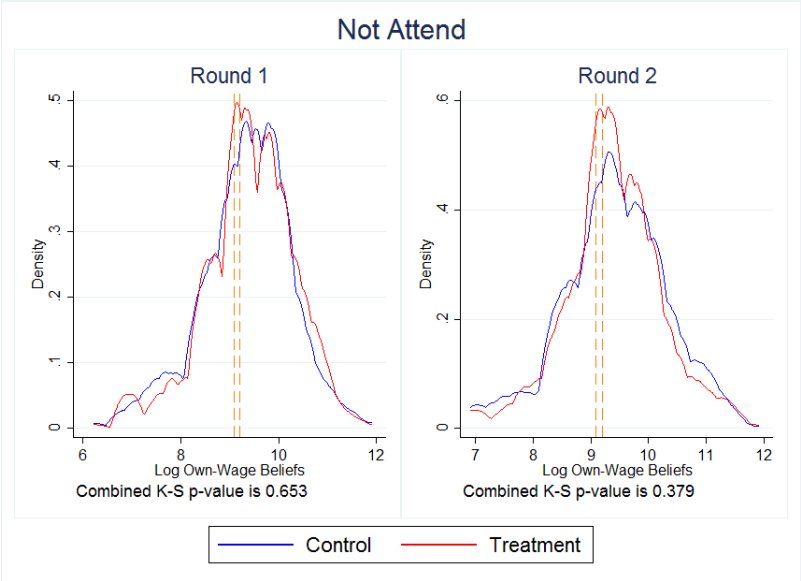


Figure 1.7: Pre and Post Distributions of Own Wage Beliefs for Non-Attendance Track; Range 1-99 Percentile

Table 1.1: % of Students Who Overestimate Earnings at Baseline

Full Sample:			
	Overall	Males	Females
Technical	71.41%	72.24%	70.43%
General	64.13%	66.06%	61.86%
Vocational	75.34%	83.39%	65.86%
Not Attend	60.79%	70.55%	49.29%
Arts:			
	Overall	Males	Females
Technical	55.49%	53.22%	57.34%
General	49.52%	49.79%	49.30%
Vocational	61.08%	71.24%	52.80%
Not Attend	53.18%	63.09%	45.10%
Commerce:			
	Overall	Males	Females
Technical	77.19%	73.19%	81.20%
General	73.35%	74.47%	72.22%
Vocational	82.52%	87.23%	77.78%
Not Attend	62.47%	72.34%	52.56%
Science:			
	Overall	Males	Females
Technical	81.72%	84.03%	77.09%
General	70.34%	71.15%	68.72%
Vocational	82.84%	88.80%	70.95%
Not Attend	66.79%	74.23%	51.96%

Table 1.2: Impact of the Information Treatment on Own Wage Beliefs for Full Sample

Panel A:	(1) Log Own Wage (Technical)	(2) Log Own Wage (General)	(3) Log Own Wage (Vocational)	(4) Log Own Wage (Not Attend)
post x treatment	-0.00742	-0.0969	-0.140**	-0.0679
	(0.0564)	(0.0592)	(0.0578)	(0.0649)
Observations	2,961	2,961	2,961	2,955
Panel B:	**Log Own Wage (Tech./NA)**	**Log Own Wage (Gen./NA)**	**Log Own Wage (Voc./NA)**	
post x treatment	0.0606	-0.0300	-0.0743	-
	(0.0638)	(0.0633)	(0.0632)	-
Observations	2,955	2,955	2,955	-
School FE	YES	YES	YES	YES
Stream FE	YES	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 106.
*** p<0.01 ** p<0.05 * p<0.1. All main effects are included.
Results are robust to addition of baseline controls.

Table 1.3: Impact of the Information Treatment on Own Wage Beliefs by Baseline Error

	(1)	(2)	(3)	(4)
	Log Own Wage (Technical)	Log Own Wage (General)	Log Own Wage (Vocational)	Log Own Wage (Not Attend)
Under-estimators:				
Panel A:				
post x treatment	0.0803	-0.0238	0.0499	0.0535
	(0.130)	(0.114)	(0.134)	(0.0992)
Observations	847	1,058	730	1,148
	Log Own Wage (Tech./NA)	Log Own Wage (Gen./NA)	Log Own Wage (Voc./NA)	
Panel B:				
post x treatment	0.146	0.0801	-0.0505	-
	(0.112)	(0.102)	(0.126)	-
Observations	1,169	1,338	897	-
Over-estimators:				
	Log Own Wage (Technical)	Log Own Wage (General)	Log Own Wage (Vocational)	Log Own Wage (Not Attend)
Panel C:				
post x treatment	-0.0434	-0.131**	-0.188***	-0.118
	(0.0565)	(0.0638)	(0.0586)	(0.0742)
Observations	2,114	1,903	2,231	1,807
	Log Own Wage (Tech./NA)	Log Own Wage (Gen./NA)	Log Own Wage (Voc./NA)	
Panel D:				
post x treatment	0.00196	-0.120	-0.0830	-
	(0.0758)	(0.0726)	(0.0713)	-
Observations	1,786	1,617	2,058	-
School FE	YES	YES	YES	YES
Stream FE	YES	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 102 (under)- 106 (over). *** p<0.01 ** p<0.05 * p<0.1. All main effects are included. Results are robust to addition of baseline controls.

Table 1.4: Impact of the Information Treatment on Own Wage Beliefs by Stream

	(1)	(2)	(3)	(4)
	Log Own Wage (Technical)	Log Own Wage (General)	Log Own Wage (Vocational)	Log Own Wage (Not Attend)
Arts:				
Panel A:				
post x treatment	0.0756	-0.140	-0.147	-0.124
	(0.130)	(0.122)	(0.136)	(0.116)
Observations	1,010	1,010	1,010	1,010
	Log Own Wage (Tech./NA)	Log Own Wage (Gen./NA)	Log Own Wage (Voc./NA)	
Panel B:				
post x treatment	0.200	-0.0159	-0.0223	-
	(0.138)	(0.125)	(0.139)	-
Observations	1,010	1,010	1,010	-
Commerce:				
	Log Own Wage (Technical)	Log Own Wage (General)	Log Own Wage (Vocational)	Log Own Wage (Not Attend)
Panel C:				
post x treatment	-0.0455	-0.182*	-0.163**	0.169
	(0.0805)	(0.102)	(0.0809)	(0.102)
Observations	917	917	917	912
	Log Own Wage (Tech./NA)	Log Own Wage (Gen./NA)	Log Own Wage (Voc./NA)	
Panel D:				
post x treatment	-0.215**	-0.349***	-0.330***	-
	(0.103)	(0.119)	(0.0904)	-
Observations	912	912	912	-
Science:				
	Log Own Wage (Technical)	Log Own Wage (General)	Log Own Wage (Vocational)	Log Own Wage (Not Attend)
Panel E:				
post x treatment	-0.0534	0.0232	-0.108	-0.218**
	(0.0725)	(0.0831)	(0.0730)	(0.110)
Observations	1,034	1,034	1,034	1,033
	Log Own Wage (Tech./NA)	Log Own Wage (Gen./NA)	Log Own Wage (Voc./NA)	
Panel F:				
post x treatment	0.167*	0.238***	0.102	-
	(0.0984)	(0.0835)	(0.0903)	-
Observations	1,033	1,033	1,033	-
School FE	YES	YES	YES	

Notes: Standard errors clustered at the survey session level. Number of clusters: 90-92 (range). *** p<0.01 ** p<0.05 * p<0.1. All main effects are included. Results are robust to addition of baseline controls

Table 1.5: Differential Impact of Information on Own Wage Beliefs for Females (By Current Stream of Study)

Dependent Variables:	(1) Log Own Wage (Tech./NA)	(2) Log Own Wage (Gen./NA)	(3) Log Own Wage (Voc./NA)
Panel A; Arts/Humanities:			
post x treatment	0.0505	-0.183	-0.205
	(0.181)	(0.137)	(0.155)
post x treatment x female	0.274	0.315	0.332
	(0.267)	(0.252)	(0.245)
Observations	1,010	1,010	1,010
Panel B; Commerce:			
post x treatment	-0.0922	-0.159	-0.208*
	(0.125)	(0.144)	(0.116)
post x treatment x female	-0.248	-0.376*	-0.235
	(0.205)	(0.218)	(0.187)
Observations	912	912	912
Panel C; Science:			
post x treatment	0.0272	0.110	-0.0899
	(0.105)	(0.0778)	(0.0861)
post x treatment x female	0.377**	0.369**	0.529***
	(0.178)	(0.166)	(0.170)
Observations	1,033	1,033	1,033
School FE	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 90.
*** p<0.01 ** p<0.05 * p<0.1. All main effects and two-way interactions included.
Results are robust to addition of baseline controls

Table 1.6: Differential Impact of Information on Own Wage Beliefs by Gender (For Over-estimators in Commerce & Science)

Dependent variable:	(1) Log Own Wage (Tech./NA)	(2) Log Own Wage (Gen./NA)	(3) Log Own Wage (Voc./NA)
Commerce-Males:			
post x treatment	-0.315**	-0.325*	-0.302***
	(0.150)	(0.169)	(0.108)
Observations	270	272	348
Commerce-Females:			
post x treatment	-0.361**	-0.655***	-0.455***
	(0.148)	(0.164)	(0.134)
Observations	329	314	323
Science-Males:			
post x treatment	0.0952	0.0105	-0.153*
	(0.132)	(0.0999)	(0.0840)
Observations	493	409	575
Science-Females:			
post x treatment	0.393*	0.363*	0.517**
	(0.204)	(0.208)	(0.193)
Observations	235	203	235
School FE	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 44-74 (range). *** p<0.01 ** p<0.05 * p<0.1. All main effects are included. Results are robust to addition of baseline controls.

Table 1.7: Revision in Own-Wage Beliefs as a Continuous Function of Baseline Error

	(1) Arts	(2) Commerce	(3) Science	(4) Arts	(5) Commerce	(6) Science
Dependent variable:	$OwnWage^T_{ijt=2} - OwnWage^T_{ijt=1}$					
Attendance Tracks:						
treatment x error	-0.00509	-0.0206*	-0.00523	-0.00548	-0.0214**	-0.00814
	(0.00945)	(0.0107)	(0.0105)	(0.00954)	(0.00916)	(0.00991)
Observations	1,473	1,344	1,494	1,473	1,344	1,494
Non Attendance Track:						
treatment x error	-0.00723	-0.00834	-0.0268***	-0.00600	-0.0160	-0.0289***
	(0.0119)	(0.0129)	(0.00997)	(0.0121)	(0.0123)	(0.00925)
Observations	491	448	498	491	448	498
School FE	YES	YES	YES	YES	YES	YES
Add. Baseline Controls	NO	NO	NO	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 88-90 (range) *** p<0.01 ** p<0.05 * p<0.1. All main effects are included.

Table 1.8: Impact of the Information Treatment on Enrollment for Full Sample

(Panel A)

Dependent Variable:	Enrollment Log-Odds
post x treatment	0.0612
	(0.126)
post x treatment x general	0.0415
	(0.112)
post x treatment x vocational	0.0425
	(0.101)
Observations (3 tracks x round)	8,880
School FE	YES
Stream FE	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 106. *** p<0.01 ** p<0.05 * p<0.1. All main effects and two-way interactions are included. Results are robust to addition of baseline controls.

Panel B–Marginal Effects on the Predicted Probability of Enrollment
(Parameter estimates from Panel A)

Technical	General	Vocational	Not Attend
-0.904%	0.856%	0.452%	-0.404%

Table 1.9: Impact of the Information Treatment on Enrollment (By Current Stream of Study)

(Panel A)

Dependent variable:	**Arts/Humanities** Enrollment Log Odds	**Commerce** Enrollment Log Odds	**Science** Enrollment Log Odds
post x treatment	0.102	-0.255	0.317**
	(0.212)	(0.210)	(0.157)
post x treatment x general	0.0617	0.162	-0.0913
	(0.191)	(0.179)	(0.163)
post x treatment x vocational	0.0416	0.283*	-0.179
	(0.184)	(0.169)	(0.144)
Observations	3,030	2,751	3,099
School FE	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 90.
*** p<0.01 ** p<0.05 * p<0.1. All main effects and two-way interactions are included.
Results are robust to addition of baseline controls.

Panel B–Marginal Effects on the Predicted Probability of Enrollment
(Parameter estimates from Panel A)

	Technical	General	Vocational	Not Attend
Arts	-1.232%	1.636%	0.451%	-0.855%
Commerce	-4.705%	1.456%	2.772%	0.477%
Science	3.456%	-0.505%	-2.283%	-0.668%

Table 1.10: Impact of the Information Treatment on Enrollment (By Current Stream of Study; Effects by Gender)

Dependent Variables:	**Arts/Humanities** Enrollment Log Odds	**Commerce** Enrollment Log Odds	**Science** Enrollment Log Odds
Panel A; Males:			
post x treatment	0.292	0.0811	0.174
	(0.287)	(0.259)	(0.193)
post x treatment x general	0.264	-0.100	-0.0386
	(0.234)	(0.191)	(0.175)
post x treatment x vocational	-0.0121	0.120	-0.203
	(0.230)	(0.213)	(0.161)
Observations	1,374	1,377	2,070
Panel B; Females:			
post x treatment	-0.0566	-0.611*	0.589**
	(0.301)	(0.322)	(0.283)
post x treatment x general	-0.0857	0.404	-0.184
	(0.281)	(0.289)	(0.310)
post x treatment x vocational	0.0823	0.454*	-0.129
	(0.264)	(0.250)	(0.270)
Observations	1,656	1,374	1,029

Notes: Standard errors clustered at the survey session level. Number of clusters: 49-77 (range). *** p<0.01 ** p<0.05 * p<0.1. All main effects and two-way interactions are included. Results are robust to addition of baseline controls.

Table 1.11: Impact of the Information Treatment on Borrowing Probability

	(1) Full Sample	(2) Arts	(3) Commerce	(4) Science
treatment	0.0665*	-0.0360	0.0571	0.147***
	(0.0353)	(0.0573)	(0.0555)	(0.0399)
mean dep. control group	0.5612	0.5447	0.5267	0.6088
Observations	1,437	491	448	498
School FE	YES	YES	YES	YES

Notes: Standard errors clustered at the survey session level. Number of clusters: 88-106 (range). *** p<0.01, ** p<0.05, * p<0.1.
Results are robust to addition of baseline controls.

APPENDIX TO CHAPTER 2

1.A Survey Details

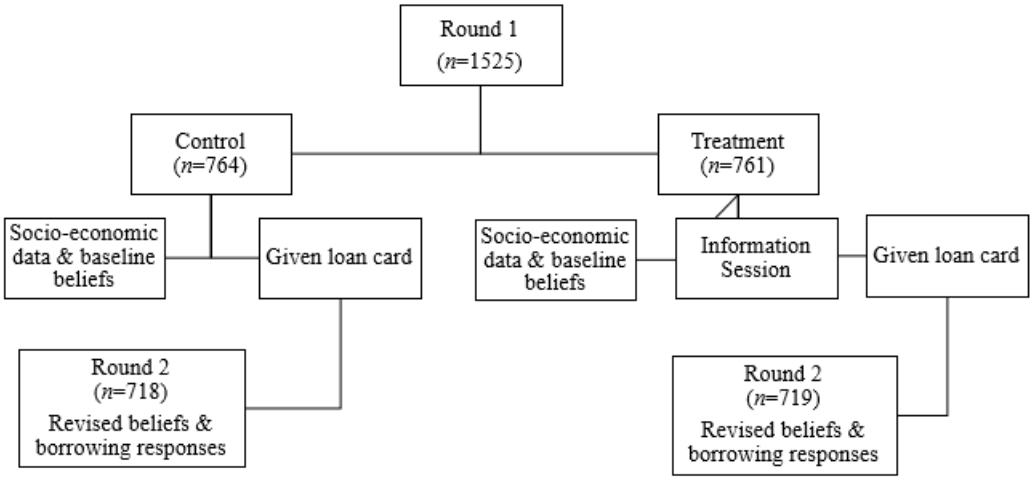


Figure 1.A.1: Survey Structure & Experimental Design

English Translation of Information Script

“ Your contribution to the first round of the survey is now over. However, before you leave we would like to talk to you about a few more things. Now onwards, you do not need to fill anything else on the tablet, only pay attention towards the screen.

You have with you the printout of the graph and table that you are seeing on the screen (**attached at the end of the script**). You are encouraged to take this home with you.

With the help of the information on the screen, we would like to provide you with some findings from recent survey data collected by the Government of India. Every few years, the Government surveys a sample of people from all Indian states and asks them about what occupation they are currently engaged in and their weekly earnings in that occupation. This survey allows us to see what the average earnings are for different individuals without having to guess or just go by what we hear from a few people. The information presented uses data on roughly 40,000 people. The data was collected between 2009 & 2012.

Now, we would like to draw your attention to the graph on the screen. This graph shows the average <u>monthly</u> earnings of four groups of people. The graph on the left side is for men and the graph on the right side is for women. According to the graph on the left, for men who have completed a technical degree, their average monthly earnings are around 22,070 rupees. Similarly, if we talk about men who have

completed a general degree, their average monthly earnings are 15,280 rupees. Those who have obtained a diploma or completed certificate course, their average monthly earnings are around 14,500 rupees and for men not studying after intermediate, their average monthly earnings are around 9,970 rupees.

Similarly, for women who have completed a technical degree, their average monthly earnings are around 16,450 rupees. If we talk about women who have completed a general degree, their average monthly earnings are 12,750 rupees. Those women who have completed a diploma or certificate course, their average monthly earnings are around 12,200 rupees and for women not studying after intermediate, their average monthly earnings are around 8,900 rupees.

It is important to keep in mind that average earnings do not imply that every individual in that group earns the average amount. Some people earn more than the average and some people earn less. For this reason, for every higher education group, we will now try to explain to you what the lower & higher amounts earned by people in that group are.

Now we would like to draw your attention towards the table in the slide. If we look at the data of men and women who have obtained a technical degree, we see that 25 percent of men earn approximately 11,780 rupees or less and 25 percent of women earn approximately 6,200 rupees or less. In the category of men who earn a technical degree, 95 percent of people, in a month, earn 51,400 rupees or less and 95 percent of women who have earned a technical degree, earn approximately 42,800 rupees or

less. This means that 51,400 rupees is the 95th percentile of men who have technical degrees and 42,800 rupees is the 95th percentile of women who earn technical degrees. This also means that very few men in this group earn more than 51,400 rupees per month and very few women earn more than 42,800 rupees per month.

*Before proceeding, ask all students if they understand the meaning of percentile and if they have any questions. (**Enumerators were encouraged to have a discussion around the concept of a percentile.**)*

Lets talk more about the data of men and women who have obtained a general degree. The 25th percentile for men in this group is 7,500 rupees and for women it is 4,500 rupees. The 95th percentile for men in this group is 36,000 rupees and for women it is around 32,120 rupees. As discussed before, this means that very few men in the group earn more than 36,000 rupees per month and very few women in this group earn more than 32,120 rupees per month.

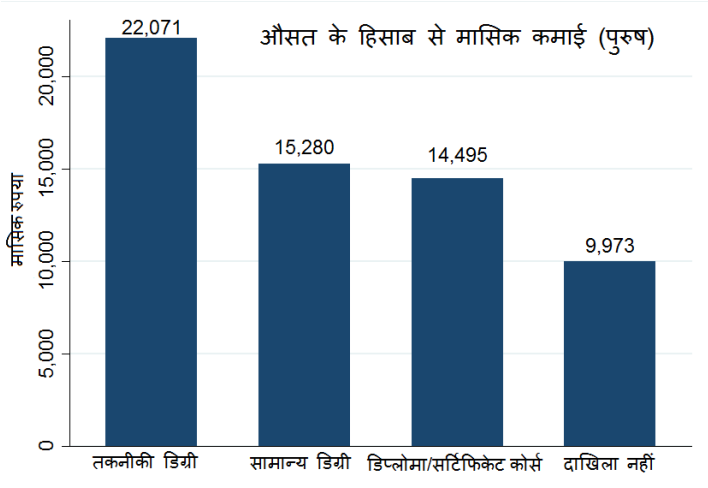
Now, lets talk about the data of men and women who have obtain a vocational degree. The 25th percentile for men in this group is around 6,430 rupees and for women it is 4,500 rupees. The 95th percentile for men in this group is 36,000 rupees and for women it is around 30,000 rupees. As discussed before, this means that very few men in the group earn more than 36,000 rupees per month and very few women in this group earn more than 30,000 rupees per month.

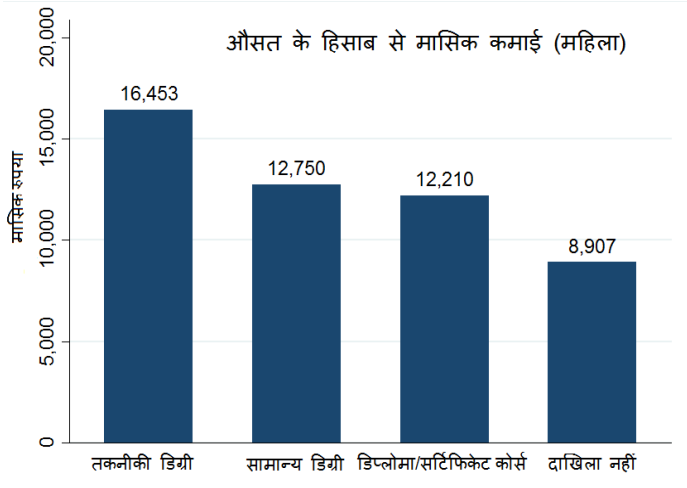
Finally, lets talk about the data of men and women who do not study beyond in-

termediate. The 25th percentile for men in this group is around 4,290 rupees and for women it is around 2,680 rupees. The 95th percentile for men in this group is around 26,000 rupees and for women it is 24,990 rupees. As discussed before, this means that very few men in the group earn more than 26,000 rupees per month and very few women in this group earn more than 24,990 rupees per month. Again, the information that we have discussed with you today, is also given in the printout that is with you. Please look at it again at home. ”

(Information Sheet on Next Page. Students in the treatment group took this sheet home and the same sheet was projected on screen during the information discussion.)

सरकारी डेटा से कुछ जानकारी





	तकनीकी डिग्री		सामान्य डिग्री		डिप्लोमा / सर्टिफिकेट कोर्स		दाखिला नहीं	
	पुरुष	महिला	पुरुष	महिला	पुरुष	महिला	पुरुष	महिला
25 प्रतिशतक[1]	11,786	6,206	7,500	4,500	6,429	4,500	4,286	2,679
95 प्रतिशतक[2]	51,429	42,857	36,000	32,117	36,000	30,000	26,001	24,990

[1] इसका मतलब है की 25 प्रतिशत पुरुष / महिला हर माह दिए गये रकम या इससे कम कमाते हैं।

[2] इसका मतलब है की 95 प्रतिशत पुरुष / महिला हर माह दिए गये रकम या इससे कम कमाते हैं।

Figure 1.A.2: Image of Information Sheet Accompanying Script

English Translation of Loan Script

"We want to place in front of you, one other hypothetical situation, for you to think at home about. Not all students are able to continue their studies after intermediate. Often, their household income is not enough for them to continue their studies or for them to enroll in a higher education program of their choice. In some such situations, bank or non-bank institutions are able to offer higher education loans, at fair interest rates, which you have to repay after completing your higher education.

Some of you must be wondering what is meant by the term interest rate. Suppose you take a loan of 100 rupees on which there is a 10% interest rate. When repaying this loan, you have to return 110 rupees. This additional 10 rupees that you pay is your interest. Fair interest rate means a rate that is neither too low or neither too high.

Please read out the questions on the loan card given to the students.

Loan for Higher Education

Q1. Suppose that someone (bank or non-bank institute) offers you a loan to enroll in a higher education course of your choice. This loan is available at a fair interest rate and you have to repay the loan only after you complete your higher education. Do you think you would want to accept such a loan?

- **Yes or No**

Q2. If yes, then how much would you like to borrow on a yearly basis? Remember, you would have to repay the loan after completing your higher education.

_____ rupees

Figure 1.A.3: Loan Card

We will ask you about your response to this question when we meet tomorrow. In the meantime, please think about this at home and if possible discuss this with your mother/father or other family members. We are very eager to learn what you think about this, so please do not forget to attend tomorrows survey session in room [**room number**] at [**time**]."

1.B Balance of Baseline Variables & Correlates of Stream of Study

Table 1.B.1: Balance of Baseline Variables

	(1) Control	(2) Treatment	(3) p-value
Age	17.24	17.30	0.19
% Male	0.53	0.55	0.45
% Scheduled Tribe	0.33	0.34	0.70
% Hindu	0.65	0.63	0.39
Asset Index	7.52	7.82	0.10
HH Facility Index	2.62	2.63	0.87
% Own Land	0.74	0.69	0.04
Board Exam Score	61.16	61.17	0.98
% Grades Repeated	0.14	0.15	0.69
% Father in Contact	0.91	0.92	0.48
% Father High School	0.18	0.20	0.22
% Father Family Business	0.11	0.14	0.11
% Father Salaried Job	0.21	0.21	0.88
% Mother High School	0.08	0.09	0.91
% Mother Housewife	0.60	0.61	0.51
Average Older Sibling Edu.	5.27	5.20	0.45
Enroll Probability (Tech)	36.96	35.27	0.24
Enroll Probability (Gen)	32.89	32.05	0.47
Enroll Probability (Voc)	22.50	24.16	0.15
Enroll Probability (NA)	7.65	8.53	0.23
% Arts Stream	0.34	0.34	0.84
% Commerce Stream	0.31	0.31	0.99
% Science Stream	0.35	0.35	0.86

Columns (1) and (2) show sample means
Column (3) shows p-values of OLS regressions on a treatment group dummy.

Table 1.B.2: Balance of Baseline Variables by Stream

	Arts			Commerce			Science		
	(1) Control	(2) Treatment	(3) p-value	(4) Control	(5) Treatment	(6) p-value	(7) Control	(8) Treatment	(9) p-value
Age	17.41	17.35	0.60	17.20	17.42	0.02	17.09	17.16	0.43
% Male	0.48	0.42	0.19	0.48	0.53	0.29	0.63	0.70	0.11
% Scheduled Tribe	0.42	0.47	0.21	0.34	0.26	0.07	0.22	0.27	0.25
% Hindu	0.56	0.47	0.05	0.63	0.65	0.66	0.75	0.75	0.96
Asset Index	6.40	6.37	0.94	7.75	8.34	0.09	8.43	8.76	0.24
HH Facility Index	2.14	2.04	0.52	2.64	2.87	0.19	3.06	2.99	0.66
% Own Land	0.74	0.73	0.74	0.66	0.58	0.07	0.79	0.75	0.20
Board Exam Score	55.74	56.09	0.69	60.77	60.41	0.72	66.82	66.70	0.91
% Grades Repeated	0.18	0.19	0.74	0.14	0.15	0.88	0.10	0.11	0.80
% Father in Contact	0.87	0.90	0.24	0.91	0.93	0.40	0.95	0.93	0.30
% Father High School	0.13	0.18	0.22	0.18	0.18	0.34	0.23	0.22	0.89
% Father Family Business	0.09	0.10	0.79	0.12	0.18	0.09	0.13	0.15	0.47
% Father Salaried Job	0.16	0.16	0.99	0.23	0.21	0.52	0.24	0.27	0.43
% Mother High School	0.04	0.05	0.62	0.05	0.09	0.11	0.16	0.12	0.22
% Mother Housewife	0.52	0.51	0.93	0.63	0.67	0.37	0.65	0.66	0.76
Average Older Sibling Edu.	4.88	4.75	0.49	5.23	5.08	0.43	5.75	5.80	0.77
Enroll Probability (Tech)	29.75	26.30	0.11	33.95	33.56	0.98	46.67	45.31	0.53
Enroll Probability (Gen)	33.85	34.46	0.77	39.72	37.70	0.34	25.93	24.83	0.58
Enroll Probability (Voc)	25.78	26.96	0.58	19.70	20.26	0.79	21.76	24.88	0.10
Enroll Probability (NA)	10.62	12.28	0.31	6.63	8.48	0.12	5.64	4.98	0.47

Notes: p-values are from OLS regressions on a treatment group dummy.

Table 1.B.3: Balance of Baseline Variables using the F-test Approach

Dependent variable:	treatment group dummy			
	All	Arts	Commerce	Science
Age	0.0137	-0.0328	0.0669*	0.0291
	(0.020)	(0.035)	(0.036)	(0.038)
% Male	-0.0237	-0.0757	0.0861	0.0171
	(0.044)	(0.075)	(0.081)	(0.091)
% Scheduled Tribe	0.0827*	0.0978	-0.0455	0.148*
	(0.050)	(0.087)	(0.091)	(0.088)
% Hindu	0.00925	-0.0519	-0.0128	0.0775
	(0.044)	(0.080)	(0.079)	(0.081)
Asset Index	0.0162**	0.0016	0.00948	0.0238*
	(0.008)	(0.016)	(0.014)	(0.013)
HH Facility Index	-0.0187	-0.00943	0.00968	-0.0274
	(0.015)	(0.028)	(0.027)	(0.027)
% Own Land	-0.0491	-0.000787	-0.0735	-0.00928
	(0.044)	(0.090)	(0.076)	(0.076)
Board Exam Score	-0.00034	0.00302	0.00113	-0.00315
	(0.002)	(0.004)	(0.004)	(0.003)
% Grades Repeated	-0.0602	0.0429	-0.151	-0.117
	(0.053)	(0.086)	(0.098)	(0.101)
% Father High School	0.077	0.13	0.0777	0.0303
	(0.047)	(0.101)	(0.084)	(0.073)
% Father Family Business	0.123**	0.0304	0.0186	0.268***
	(0.062)	(0.134)	(0.108)	(0.100)
% Father Salaried Job	0.0458	-0.0718	0.0796	0.0881
	(0.052)	(0.111)	(0.097)	(0.080)
% Mother High School	-0.0191	0.151	0.0155	-0.109
	(0.068)	(0.182)	(0.138)	(0.089)
% Mother Housewife	0.0153	-0.101	0.0712	0.0371
	(0.041)	(0.077)	(0.078)	(0.068)
Average Older Sibling Edu.	-0.0173	0.000116	-0.0443*	-0.0206
	(0.012)	(0.021)	(0.023)	(0.023)
Enroll Probability (Tech)	-0.0026	-0.00338	-0.00363	0.00433
	(0.001)	(0.002)	(0.003)	(0.003)
Enroll Probability (Gen)	-0.00226	-0.00426*	-0.00334	0.00561
	(0.001)	(0.002)	(0.003)	(0.004)
Enroll Probability (Voc)	-0.00178	-0.00283	-0.0034	0.00522
	(0.002)	(0.002)	(0.003)	(0.003)
School Fixed Effects	Yes	Yes	Yes	Yes
F-test that all coef. are 0	1.340	0.910	1.160	1.116
p-value of F-test	0.153	0.564	0.298	0.295

Table 1.B.4: Correlates of Students' Current Stream of Study

	Mean(Commerce)-Mean(Arts)		Mean(Science)-Mean(Arts)		Mean(Science)-Mean(Commerce)	
	(1) Diff. in Mean	(2) p-value	(3) Diff. in Mean	(4) p-value	(5) Diff. in Mean	(6) p-value
Age	-0.068	0.325	-0.257	0.000	-0.188	0.002
% Male	0.052	0.102	0.217	0.000	0.165	0.000
% Scheduled Tribe	-0.149	0.000	-0.201	0.000	-0.052	0.064
% Hindu	0.117	0.000	0.235	0.000	0.118	0.000
Asset Index	1.657	0.000	2.212	0.000	0.554	0.013
HH Facility Index	0.662	0.000	0.934	0.000	0.271	0.019
% Own Land	-0.112	0.000	0.036	0.171	0.148	0.000
Board Exam Score	4.682	0.000	10.850	0.000	6.168	0.000
% Grades Repeated	-0.042	0.079	-0.081	0.000	-0.039	0.066
% Father in Contact	0.035	0.063	0.050	0.004	0.015	0.344
% Father High School	0.024	0.339	0.069	0.007	0.045	0.091
% Father Family Business	0.057	0.013	0.049	0.023	-0.009	0.724
% Father Salaried Job	0.065	0.019	0.097	0.000	0.032	0.267
% Mother High School	0.032	0.033	0.098	0.000	0.066	0.001
% Mother Housewife	0.129	0.000	0.136	0.000	0.007	0.813
Average Older Sibling Edu.	0.341	0.007	0.950	0.000	0.609	0.000
Enroll Probability (Tech)	5.718	0.000	17.950	0.000	12.232	0.000
Enroll Probability (Gen)	4.558	0.004	-8.775	0.000	-13.333	0.000
Enroll Probability (Voc)	-6.388	0.000	-3.038	0.036	3.350	0.013
Enroll Probability (NA)	-3.889	0.000	-6.137	0.000	-2.248	0.003

Table 1.B.5: Baseline Relationship between Enrollment Intentions & Own Wage Beliefs

Dependent variable:	Probability of Enrollment							
	(1) All	(2) Arts	(3) Commerce	(4) Science	(5) All	(6) Arts	(7) Commerce	(8) Science
prob. enjoy coursework	0.444***	0.317***	0.450***	0.548***				
	(0.0244)	(0.0395)	(0.0490)	(0.0377)				
graduation prob.	0.142***	0.217***	0.179***	0.0258				
	(0.0262)	(0.0419)	(0.0491)	(0.0438)				
prob. parental approval	0.256***	0.218***	0.261***	0.262***	0.417***	0.411***	0.426***	0.393***
	(0.0241)	(0.0421)	(0.0448)	(0.0381)	(0.0127)	(0.0228)	(0.0240)	(0.0202)
employment prob.	0.123***	0.0506	0.0878*	0.227***	0.181***	0.111***	0.164***	0.264***
	(0.0284)	(0.0470)	(0.0526)	(0.0453)	(0.0209)	(0.0340)	(0.0390)	(0.0353)
log own wage	2.320***	0.0836	2.711**	4.204***	2.033***	0.145	2.659***	3.843***
	(0.733)	(1.102)	(1.268)	(1.491)	(0.525)	(0.813)	(0.931)	(1.045)
Constant	-49.51***	-15.17	-54.98***	-77.15***	-26.98***	-2.594	-33.63***	-49.88***
	(7.130)	(10.60)	(12.52)	(14.64)	(4.748)	(7.314)	(8.405)	(9.553)
Observations (student x track)	4,572	1,557	1,407	1,608	6,092	2,076	1,873	2,143
R-squared	0.472	0.382	0.473	0.572	0.344	0.249	0.352	0.431
Non-Attendance Track	NO	NO	NO	NO	YES	YES	YES	YES
Attendance Tracks	YES	YES	YES	YES	YES	YES	YES	YES
Student FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

1.C Further Results

Table 1.C.6: OLS & Quantile Regressions of Baseline Error on Stream of Study

Dependent variable:	$error^T$					
	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q95
Technical Track:						
Arts	-5.438***	-0.585***	-18.71***	-1.620***	-0.193**	-0.516***
	(0.640)	(0.172)	(0.116)	(0.287)	(0.0980)	(0.169)
Commerce	-0.885	-0.0543	0	-0.280	-0.0219	-0.138
	(0.539)	(0.190)	(5.310)	(0.209)	(0.115)	(0.134)
Mean for Science	6.843***	-9.793***	8.676***	10.49***	10.95***	11.89***
	(0.354)	(0.175)	(0.0937)	(0.141)	(0.0743)	(0.116)
General Track:						
Arts	-4.296***	-0.438***	-3.387***	-16.20**	-0.292***	-0.183**
	(0.715)	(0.132)	(0.210)	(7.384)	(0.0991)	(0.0800)
Commerce	0.532	0.148	0	0	0	0
	(0.605)	(0.173)	(6.464)	(0.165)	(0.108)	(0.146)
Mean for Science	4.621***	-9.586***	-6.328***	9.875***	10.58***	11.40***
	(0.430)	(0.136)	(0.220)	(0.120)	(0.0524)	(0.0731)
Vocational Track:						
Arts	-4.253***	-0.894***	-18.10***	-0.843***	-0.218	0.135
	(0.628)	(0.196)	(0.214)	(0.213)	(0.143)	(0.145)
Commerce	0.104	0	0.479	0.192*	0.0858	0.135
	(0.526)	(0.201)	(0.319)	(0.100)	(0.0915)	(0.131)
Mean for Science	6.868***	-9.104***	8.627***	10.15***	10.84***	11.52***
	(0.352)	(0.200)	(0.211)	(0.101)	(0.0821)	(0.0956)
Non-Attendance Track:						
Arts	-2.421***	-0.342***	-0.537***	-4.318*	0	-0.0761
	(0.662)	(0.0664)	(0.193)	(2.491)	(0.0825)	(0.178)
Commerce	-0.682	0	-0.296	-0.618	0.101	-0.0513
	(0.625)	(0.111)	(0.262)	(0.760)	(0.0818)	(0.166)
Mean for Science	2.976***	-9.301***	-8.668***	8.307***	9.906***	11.29***
	(0.456)	(0.0742)	(0.197)	(0.660)	(0.0509)	(0.137)
Observations	1,524	1,524	1,524	1,524	1,524	1,524

Notes: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Reference category is Science.

Table 1.C.7: Probability of Non-Attendance by Stream

	Unconstrained Choice Set		Constrained Choice Set	
	(1)	(2)	(3)	(4)
Dependent Variable:	NA prob.	NA prob.	NA prob.	NA prob.
Arts	5.992***	4.574***	6.551**	0.887
	(0.968)	(1.043)	(2.999)	(3.347)
Commerce	2.131***	1.372*	9.214***	6.549**
	(0.766)	(0.802)	(3.095)	(3.184)
School FE	YES	YES	YES	YES
Baseline Controls	NO	YES	NO	YES
Observations	1,524	1,524	1,524	1,524

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Reference category is Science.

Table 1.C.8: Effect of the Treatment on Own-Wage Belief Updating (by Baseline Enrollment Probability)

	Unconstrained Choice Set		Constrained Choice Set	
	(1)	(2)	(3)	(4)
Dependent variable:	$\mid OwnWage^{T}_{ijt=2} - OwnWage^{T}_{ijt=1} \mid$			
treatment#baseline enroll. prob.	0.000616	0.000616	-0.000885**	-0.000885**
	(0.000667)	(0.000671)	(0.000434)	(0.000437)
School FE	YES	YES	YES	YES
Track FE	YES	YES	YES	YES
Baseline Controls	NO	YES	NO	YES
Observations	3,784	3,784	3,784	3,784

Notes: Clustered Standard Errors in Parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
All main effects are included in the model. Sample restricted to Commerce & Science.

CHAPTER 2

DO STUDENTS OVERESTIMATE POST-SECONDARY EDUCATION EXPENSES? INSIGHTS FROM SUBJECTIVE & MEASURED INDIAN DATA

2.1 Introduction

An increasing amount of recent economics literature is interested in analyzing beliefs about the benefits and costs of education, that students' subjectively perceive, prior to the point of making a critical investment in human capital. One use of eliciting such subjective beliefs is to estimate standard education choice models, wherein individuals decide on entering a given level of education by weighing benefits against costs[1], using subjective expectations data rather than actual choice data (Manski (2004), Wiswall and Zafar (2015), Delavande and Zafar (2014)). Here, the use of subjective expectations, on all alternatives in an individuals' choice-set, helps circumvent assumptions about expectation formation and does not assume a mapping between revealed elements of education utility to beliefs about these elements at the time the decision was made. Another point of interest in data about subjective beliefs, which is perhaps more directly amenable to policy intervention, is analyzing the accuracy of beliefs. Given that individuals' subjective beliefs are conditioned on their information sets, imperfect information about some aspect of the benefit or cost of education is seen as a barrier to education access (Jensen (2010), Oreopoulos and

[1]See Willis and Rosen (1979) & Altonji (1993) for more traditional approaches using revealed preference data.

Dunn (2013) Dinkelman and Martínez (2014), Hastings, Neilson and Zimmerman (2015)).

The accuracy of students' beliefs about the costs associated with post-secondary education is of primary interest in this paper. The recent literature on analyzing the accuracy of subjective beliefs regarding education is concentrated more heavily on the side of studying beliefs about the subjective benefits of education, more specifically, expected labor market benefits. This includes earlier inquiries by Betts (1996), and more recent experimental investigations that examine changes in education investments upon randomizing information on population earnings (Nguyen (2008), Jensen (2010), Fryer Jr (2013), Loyalka et al. (2013), Oreopoulos and Dunn (2013), Pekkala Kerr et al. (2015)). The literature on the accuracy about beliefs regarding other elements of an individual's education utility function, including beliefs about costs, is relatively scarce[2].

In this paper I combine two datasets to draw insights about the extent and implications of overestimating post-secondary expenses. The first is a self-collected dataset on high school students' beliefs regarding post-secondary expenses, conditional on track, elicited 5-9 months before students make an actual decision about post-secondary enrollment. This data was collected from students studying in schools located in the east Indian state of Jharkhand. The second is a nationally representa-

[2]Some research indicates the importance of providing information about financial aid opportunities and eligibility for financial aid (Dinkelman and Martínez (2014)) as well as simplifying the process of applying for aid in the U.S. (Bettinger et al. (2009)) in reducing high-school absenteeism and increasing college-enrollment, respectively.

tive dataset on post-secondary expenses incurred by students studying in the same tracks. Fortuitously, both datasets were collected during the same year. I use the nationally representative dataset on measured expenses as a reference distribution to determine the accuracy of students' cost beliefs. Naive comparisons indicate that students' perceived costs are considerably higher than measured costs, especially for general academic degrees, which are substantially cheaper than the other two tracks–technical and vocational. However, comparing every individual's perceived costs to an overall distribution of measured expenses disregards the possibility that some people may rationally expect costs to be lower or higher for them, given their personal characteristics. To address this, I assign to every individual a measured cost, from the nationally representative data, of a person most similar in "type to them, using a set of SES characteristics that overlap both datasets. Using naive and person-specific predictions of measured costs, for every individual, along with their cost perceptions and budget for education expenses, I describe the implications of students' cost beliefs in determining their perceived affordability for each type of post-secondary education. Given that students may acquire more information about tracks most preferred by them, I also estimate a flexible model of track-choice to estimate each student's utility maximizing track. With this, I draw implications of students' errors regarding post-secondary costs, in determining their perceived affordability, for their most preferred or utility maximizing track.

This paper uniquely combines three pieces of subjective beliefs data–students' beliefs regarding the cost of education, students' beliefs about their capacity to pay

for this type of education and students' beliefs about out of pocket expenses net of scholarships/stipends. This helps us draw insights that add to the limited literature analyzing subjective cost beliefs. Two papers are of notable interest here. Bleemer and Zafar (2015) randomize information about the average annual net cost of attending a 4-year public university and that of a 4 year nonprofit private university, in 2014, in the United States. They find that, on average, U.S. household heads overestimate the costs associated with public colleges and revise beliefs about their child's college costs as a result of the cost information, but do not revise expectations regarding college enrollment. The paper cannot comment on misperceptions regarding cost beliefs relative to household's budget and ability to pay for college, which might be one reason for why the authors do not see an increase in expected college enrollment. Hastings et al. (2015) provide descriptive insights on the link between overestimation of college costs and matriculation in a degree program in Chile[3]. They show that those who overestimate costs by at least 25% are 5.5 percentage points less likely to matriculate in a degree program, as compared to those who perceive costs accurately. However, because they cannot rule out that other determinants of matriculation may be correlated with cost overestimates, it is not clear whether students who did not matriculate did so because they believed that college was unaffordable or because those who overestimated costs were also limited in their ability to matriculate in other ways. While the approach adopted in this paper is also descriptive, it addresses more directly the link between overestimation

[3]Hastings, Neilson and Zimmerman (2015) also have an experimental paper, a companion to the descriptive piece, which randomizes information on earnings and costs together, and does not address imperfect information about costs separately.

of costs and perceptions about affordability. Moreover, Hastings et al. (2015) cannot comment on the extent to which students' deviations of perceptions from "actual" costs reflects their private information about aid access.

In my analysis I find that students perceived expenses of post-secondary education are substantially higher than measured expenses, though track-specific differences are substantial. The average difference between the two is the highest for general academic degrees, where the ratio of the median of perceived to measured expenses is over 6, compared to a ratio of 1.4-1.03 for technical and vocational tracks, respectively. While students do accurately perceive the ranking of expenses of the three different tracks, they do not perceive correctly the extent to which costs differ, by track. For instance, in the measured data, general degrees are 7.6 times cheaper than technical tracks and roughly 6 times cheaper than vocational tracks. However, students perceive that general degrees are around 1.6 times cheaper than technical tracks and cost almost equal to vocational tracks (are 1.02 times cheaper). I estimate that if students perceived expenses more accurately, then their perceived affordability for technical tracks and general tracks would increase by 10 percentage points and 55 percentage points, respectively, though for vocational tracks students already have accurate perceptions about costs. Also, students have relatively more accurate beliefs about the expenses associated with their utility maximizing track or their most preferred track, which I estimate using a flexible model of track-choice. If students perceived expenses more accurately, then 15 percentage point more people would believe their utility maximizing track to be affordable to them, though all of

this increase is on account of general degrees.

A few issues need to be addressed headfirst. The first regards parental beliefs about educational expenses and how they differ from their children's. That we lack data on this is a weakness of the data. Nevertheless, previous research indicates the importance of adolescent beliefs in determining attendance at higher levels of education. Attanasio and Kaufmann (2009) use subjective expectations data from Mexico to simultaneously control for youth and parents' expectations of earnings in determining high school and college enrollment decisions. They find that while both expectations matter for high school enrollment, only the youths' expectations matter for college enrollment. Other papers that show important agency of children relative to parents in education decisions include Berry (2015), Giustinelli (2016) and Dinkelman and Martínez (2014). Youth may also be more informed than their parents on account of being more educated–67% of fathers and 87% of mothers are less educated than their children for my sample of youth. Another issue has to do with the timing of collection of beliefs data. It is likely that students will acquire more information about costs at the time of making at actual decision. While this is true, students and their families might be less likely to acquire information about tracks that they consider unaffordable to begin with and beliefs held at prior stages may impact prefigurative and preparatory commitment (Grodsky and Jones (2007)) and intermediate decisions. A final comment concerns interchangeable use of perceived "expenses" versus "costs" in this paper. While I use both terms, strictly we are referring to expenses incurred here and not the sticker prices of degrees and other items of expenditure.

The rest of the paper proceeds as follows: section 2.2 provides some institutional background, section 2.3 discusses details of both data sources used, section 2.4 describes estimation, section 2.5 presents results and the final section concludes.

2.2 Background

Figure 2.1 presents descriptives on the proportion of Indians attending post-secondary education[4]. As is apparent, a strong wealth gradient exists in post-secondary enrollment. Unconditionally, only 6% of individuals belonging to the poorest wealth quintile enroll, compared with 32% in the richest wealth quintile. Conditional on high school completion, this proportion varies from 52% to 76% between the poorest and richest quintiles.

Broadly, post-secondary education consists of three tracks in the country– (i) technical or professional degrees, (ii) general academic degrees and (iii) vocational diplomas or certificate courses. Technical degree courses include professional degrees in fields like medicine, engineering and architecture as well as "job-oriented degrees like Bachelors of Computer Application, Business Administration, Information-Technology (IT), Pharmacy or Hotel Management. These degrees are regulated by the All-India Council for Technical Education (AICTE). The majority of individuals enrolled

[4]Kaufmann (2014) compares some Latin American countries with the OECD in terms of attendance rates in the 18-24 age group. Attendance rates in India, at 18%, are somewhat higher than Brazil's (16%), but are lower than those of Colombia, Peru, Mexico and Chile. The OECD average is 56%.

in technical degrees attend private institutions. General degree courses are non-technical and award a bachelors degree in either the arts, sciences or commerce, further categorized according to subject. A little less than half of all students enrolled in these degrees attend private institutes. Vocational courses are not academic and focus on imparting a set of skills (rather than broader academic knowledge) targeted towards employment in a specific sector. Under the government, these courses are offered either by Industrial Training Institutes/Centers (ITI/ITC) or by Polytechnics. The fraction of students enrolled in private institutes for each degree are given in Table 2.1. It is important to note that the fraction of private institutes in Jharkhand is much lower than the all-India average for technical and general tracks, but slightly higher for vocational tracks.

Measured wage premiums for technical degrees are more than a 100% of the wages of those who complete high school. Despite the fact that vocational training is more expensive than general degree courses, wage premiums for vocational courses (42% of high-school wage) are around 8 percentage points lower than the wage premiums for general courses.

Admissions into post-secondary education involve a mix of applications based on final scores in 12th grade examinations and institute-specific written examinations. Students' apply to a attend specific degree-institute pairs. The elicitation of subjective data in this paper took place prior to students took their final 12th grade exams or applied to post-secondary institutes. The strong wealth gradient in post-secondary enrollment in part owes to the lack of systematic financial aid to attend

such education. Between 16-20% of individuals receive some type of scholarship in the country and in Jharkhand this fraction is even lower (2-7%). More details about the fraction of students receiving scholarships and waivers are discussed in section 2.3.2.

2.3 Data

This analysis makes use of two datasets–one measures subjective beliefs regarding post-secondary education expenses, and the second collects actual data on post-secondary expenses faced by students enrolled in this type of education. The first dataset on subjective beliefs is a self-collected dataset on 1525 12th grade students[5] drawn from 9 government schools in the east Indian state of Jharkhand, and was collected between October 2014 and February 2015. Hereafter, it is referred to as the "survey sample". The second dataset was collected by the Indian government's National Sample Survey Office (NSSO) between January-June 2014, with the objectives of garnering data on the (a) participation of persons aged 5-29 years in the pursuit of education, and (b) private expenditure incurred on the education of house-

[5]Specifically, these students were studying in the final year of their "intermediate degree" in what are known as "intermediate colleges". After completing 10th grade, students chose between attending either an "intermediate college, for two years of higher-secondary schooling, or attending a high school which offers 11th and 12th grades. Public "intermediate colleges, like the ones surveyed here, are often co-located with public colleges offering undergraduate degrees. Since intermediate education is equivalent to higher secondary education, I refer to these students as being in 12th grade, throughout the paper, and also refer to the "intermediate colleges" as "government/public schools", to avoid confusing terminology as most people think of colleges as referring to only post-secondary education. All 9 government schools in this survey are affiliated with Ranchi University, a large state university.

hold members. This NSSO dataset is also referred to as the 71st NSS round, here we simply refer to it as the "NSS dataset". The close overlap in the timing of the collection of the two datasets is fortuitous–nationally representative data on education expenses is rarely collected in the country (it was last collected a decade ago in 2007-08) and more regularly collected datasets on overall consumption expenditures, would be unsuitable for the current analysis. Firstly, they do not contain detailed measures of education expenses and, secondly, they do not follow a sampling frame that yields sufficient observations on post-secondary students in the country.

2.3.1 The Survey Sample

The first dataset, the survey sample, was collected with the explicit intention of examining in detail subjective beliefs regarding post-secondary education, of 12th grade students, 5-9 months (depending on survey date) before graduating from high-school and making an actual decision regarding enrollment in post-secondary education. A total of nine schools participated in the survey. Four of the nine schools are situated in the capital city of Ranchi, one in a rural block of Ranchi district and four others are in surrounding rural districts. We drew, approximately, an equal number of students from each school. Further, within each school, students were randomly assigned to survey-sessions of 15 students each. An information experiment was embedded in the survey, with survey-sessions being assigned to either a control session or a treatment session. However, the current analysis, makes use only of the baseline

data, which was collected identically across both groups. Details of the experiment are in a separate paper, here we focus on baseline variables most relevant to the current analysis.

The baseline survey consisted of two main modules- the first module was focused on collecting socio-economic details of the students and the second was focused on belief elicitation about different aspects of post-secondary education. Among the socio-economic variables, we collected data on student gender, caste, religion, a household assets and facilities module, parental education and occupation, older sibling gender and education, scores on previous centralized board examinations and history of grade repetition. In the second part, belief elicitation was contingent on each post-secondary alternative i.e. technical/professional degrees, general degrees, vocational diplomas/certificate courses and the fourth alternative of not attending further education after 12th grade. The three post-secondary education tracks were constructed to maintain consistency with classifications maintained by National Sample Survey Office. Nevertheless, for elicitation purposes, the categories are broad and encompass a variety of courses of study. Therefore, data collection was preceded by a detailed explanation of possible courses/degrees that are part of every category. Since a majority of the beliefs questions were either probabilistic in nature or required students to express responses on a scale of 0-100, the baseline beliefs module was also preceded by a discussion (with examples) on answering probabilistic questions.[6]

[6]We ensured that answers to all probabilistic questions sum to 100 by placing the total as a constraint in the questionnaire, without fulfilling which, the survey would not proceed to the subsequent question.

In the baseline beliefs module, stated probabilities of enrollment were elicited by specifying all three post-secondary alternatives as being in all individuals' feasible choice-set.[7] Next, individuals were asked about certain non-pecuniary and pecuniary beliefs conditional on hypothetical enrollment in each alternative. Pecuniary beliefs included data on expected probability of employment and expected average monthly earnings at age 30.[8] Non-pecuniary beliefs included questions regarding likelihood of enjoyment of coursework (0-100 scale), likelihood of parental approval of education track (0-100 scale) and likelihood of being able to pass (graduate from) the course/degree (0-100 scale). I use this data to estimate each individual's utility maximizing track, as described in section 2.4.1.

Finally, the two most important survey questions from the point of view of this analysis concern the elicitation of beliefs regarding post-secondary expenses and beliefs regarding students' budgets for post-secondary study. The elicitation of beliefs regarding expected post-secondary expenses, by track, stressed that students must express beliefs about yearly out-of-pocket expenses, including course fee and other miscellaneous costs. The exact wording was:

[7]The exact wording of the question used to elicit enrollment probabilities for potentially hypothetically choice sets of individuals was: *"Think ahead to next year when you have completed (sic) intermediate. Imagine that you have passed your (sic) intermediate examinations and are able to secure admission in one degree/course belonging to each of the options 1, 2 and 3. Option 4 is also available to you. Suppose that you are provided with financial aid such that all your expenses (tuition, boarding, room, etc.) are paid for at a private/government institute for a course belonging to each options 1, 2 and 3. State the percent chance that you would enroll in each of the following?"* This statement was followed by the four education options among which students had to allocate probabilities.

[8]For e.g. the question used to elicit own earnings beliefs was: *Consider the situation where you graduate from a degree belonging to the alternative insert track. Look ahead to when you will be 30 years old. Think about the types of jobs associated with degree/course. How much do you think YOU would earn per MONTH on AVERAGE, if you completed a degree of this type?*

[1] *"Think about the yearly expenses (including fees, hostel and other expenses associated with a degree/course belonging to each of the three alternatives listed below. If you are enrolled in a degree/course belonging to each alternative (in an institute/college of your choosing), then how much do you think that you and your family would have to spend on a yearly basis? If scholarships/loans are possible, please subtract the amount you are likely to receive: 1. Technical/Professional degree 2. General degree 3. Vocational diploma/certificate course."*

To elicit beliefs about students' yearly budget or maximum feasible amount that they expect to be able to pay for post-secondary education, the following question was posed:

[2] *"What is the maximum yearly amount (including fees, hostel and other expenses) that you and your family would be able to pay, for you to be enrolled in a degree/course after intermediate, without taking any loan?"*

2.3.2 NSS Data

The NSS dataset provides us with estimates of actual expenses incurred by individuals pursuing post-secondary education in the country, and serves as a reference distribution for comparison with high-school students' perceptions about expenses from the survey sample. The survey collects expenditure data from 5-29 year old

individuals currently attending education at the primary level and above.[9] As listed in Table 2.1, total expenditure for a year is collected as a sum of item-wise expenses on (i) course fee[10], (ii) books, stationery and uniform, (iii) transport, (iv) private coaching and (v) other expenses. The "other expenses" category includes miscellaneous expenses such as payment for a study tour or a compulsory "donation" (often a bribe) paid for which no valid receipt was provided. Though the elicitation of subjective beliefs in the survey-sample emphasized that students report their perceptions about total yearly expenses, the item-wise break-down of expenses collected in the NSS data is more detailed than in the survey sample. This difference in format works against us being able to establish over-estimation of education expenses on the part of students in the survey sample. 97% of all courses are full-time courses, and 94% of courses have a minimum duration of 12 months. The NSS data, for the purposes of calculating yearly expenses, is limited to this sample.

Table 2.1 provides summary statistics on item-wise and total yearly expenses. Total expenditure on the general track is several folds lower than on technical degrees and vocational diplomas. Median yearly expenses incurred in pursuing a general degree are 6 times lower than expenses associated with technical degrees, and 3 times lower than expenses on vocational diplomas. The difference in course fees for the general track, as compared to the other two tracks, is even starker. Median course fees for the technical track are over 12 times higher than for the general track and the median

[9]Data is collected for one "basic course" per individual, defined by a list of criteria to circumvent ambiguity. For instance, If an individual is pursuing more than one course, then the course which is at the highest level is considered to be the basic course.

[10]includes tuition fee, examination fee, development fee and other compulsory payments

course fee for vocational tracks are 6 times higher than for the general track. In line with the all-India numbers, pursuing a general degree in Jharkhand is much cheaper than technical and vocational tracks–the former is almost 7.5 times more expenses and the latter over 6 times. For technical and vocational tracks, course fees form the highest item of expenditure followed by money paid for private tuition. Expenses on private coaching are even higher than regular course fee for those in general tracks.

To maintain comparability with the elicitation of out-of-pocket expenses in the survey sample, expenses net of scholarships, stipends and reimbursements are calculated. The fraction of students receiving scholarships is 16.5%-20% at the all-India level, but relatively small (2%-7%) in Jharkhand (Table 2.1). However, for those who receive scholarships, the amount received is relatively large–on average about a third of total yearly expenses. A small fraction of students also receive some amount of tuition waivers and subsidies for textbooks. The expenses recorded in the NSS data are amounts actually incurred by households. Another piece of useful data in the NSS regards whether students attend government or private institutes, which constitutes an important source of variation in total expenses incurred. While students' beliefs about expenses are not elicited separately for government and private institutes, I use this piece of information from the NSS dataset to compare students' perceived belief distributions to two separate distributions of actual expenses, government and private, providing illustrative extremes around the extent of overestimation of expenses on the part of students.

The NSS dataset also collects a rich set of variables on household characteristics,

including measurement of socio-economic status (SES). I include in my analysis, SES variables that overlap with those collected in the survey sample. This includes student gender, caste, religion, parental education and household occupation, as well as state of residence. These SES variables are used to make out of sample predictions of measured costs from the NSS data to students in the survey sample, as described in further detail in section 2.4.2.

2.4 Estimation

2.4.1 Estimating Students' Utility Maximizing Track

While we collect data on every students' beliefs regarding post-secondary expenses for each of the three tracks, it is additionally informative to investigate the extent to which students' beliefs about expenses impacts their perceptions about the affordability of the track that they would most prefer to pursue. Towards this end, I estimate students' utility maximizing track using data on their stated enrollment probabilities across track, track-specific beliefs about pecuniary factors (expected earnings at age 30 and likelihood of finding employment) and non-pecuniary factors (likelihood of enjoying associated coursework, of being able to graduate and of parental approval), as well as student-specific co-variate controls.

The estimating equation is derived from a model of utility maximizing behavior and

I follow the estimation procedure recommended in (Blass, Lach and Manski (2010)) for the modeling of elicited choice-probabilities.

The utility that student i derives from pursuing track j with $j = 1, ..J$, has the random-coefficients form:

$$U_{ij} = x_{ij}\beta_i + \varepsilon_{ij} \tag{2.1}$$

where $x_{ij} = x(v_{ij}, s_i)$ is a function of observed track-specific beliefs (v_{ij}) and student-specific attributes (s_i). Stated choice analysis asks that student i provide to the researcher a utility maximizing choice and hence the implicit assumption is that i knows the value of both x_i and ε_i. On the other hand, eliciting choice probabilities enables respondents to express uncertainty about ε_i. Blass, Lach and Manski (2010) call this "resolvable uncertainty" or uncertainty about variables that the student does not know at the time of elicitation but expects to know at the time of making an actual choice.

Given a subjective distribution for ε_i, student i derives the subjective probability that they would chose j and reports this as their choice probability q_{ij}. Therefore, with the utility function in Equation 2.1 the subjective choice probability q_{ij} is given by:

$$q_{ij} = Q_i[x_{ij}\beta_i + \varepsilon_{ij} > x_{ik}\beta_i + \varepsilon_{ik}], \qquad all \quad k \neq j] \tag{2.2}$$

To estimate Equation 2.2 using elicited choice-probabilities, an i.i.d extreme value distribution can be assumed for Q_i (or ε_i) which is restrictive, but in line with the assumption made in much of the choice-modelling literature. With this, the choice probabilities have the following multinomial logit form:

$$q_{ij} = \frac{e^{x_{ij}\beta_i}}{\sum_{h=1}^{j} e^{x_{ih}\beta_i}}, \qquad j = 1, ..J \tag{2.3}$$

To model the probability of pursuing track j relative to a base alternative 1 (in this case non-attendance), a log odds transformation to Equation 2.3 can be applied, which yields:

$$ln\Big(\frac{q_{ij}}{q_{i1}}\Big) = (x_{ij} - x_{i1})\beta_i, \qquad j = 2, ..J \tag{2.4}$$

Equation 2.4 is of the linear mixed-model form which can also be written in an error-components format with $\beta_i = b + \eta_i$. Therefore we have:

$$ln\Big(\frac{q_{ij}}{q_{i1}}\Big) = (x_{ij} - x_{i1})b + u_{ij}, \qquad j = 2, ..J \tag{2.5}$$

with $u_{ij} = (x_{ij} - x_{i1})\eta_i$. u_{ij} is the stochastic portion of the utility which introduces correlation in utility across tracks and within student. Hence, estimation of this type does not suffer from the restrictive "Independence of Irrelevant Alternatives (IIA)"

property of multinomial logit (Train (2003)). The mean-zero assumption $E(\eta) = 0$, implies that $b = E(\beta)$, $E(u|x) = 0$ and Equation 2.5 yields the linear mean regression model (OLS with random effects):

$$E\Big[ln\Big(\frac{q_{ij}}{q_{i1}}\Big)|x\Big] = (x_{ij} - x_{i1})b \tag{2.6}$$

In the first specification, Equation 2.6 is used to estimate students' utility maximizing track. With stated choice-analysis (or when only observation per individual is observed) parametric assumptions about the shape of β need to be made in order to estimate a mixed-logit model which does not suffer from the IIA assumption. Here, this parametric assumption is not made.

The log-odds function is sensitive to choice-probabilities at the [0,1] boundaries, generating log-odds that are equal to minus or plus infinity. To avoid dropping these observations, 0 and 1 values are replaced with values near to these boundaries. This can bias least-square estimates. Therefore, Blass, Lach and Manski (2010) recommend estimating a median regression, which is robust to order preserving replacements. This forms our second specification of estimating students' utility maximizing track.

$$M\Big[ln\Big(\frac{q_{ij}}{q_{i1}}\Big)|x\Big] = (x_{ij} - x_{i1})b \tag{2.7}$$

2.4.2 Predicting Expenses from NSS Data

The second piece of econometric analysis that requires some explanation is the out of sample prediction of expenses from the NSS dataset, to the survey sample of students from Jharkhand. The basic idea is to assign to each individual a value of "measured expenses", which most closely approximates the expenses faced by students of their "type". This is to facilitate a comparison of more *relevant* "measured expenses" with the students' "perceived expenses". For example, out-of-pocket post-secondary expenses likely differ by caste in India, because the Indian government sometimes[11] provides scholarships or stipends to students from socially disadvantaged castes. Hence, it makes sense to compare perceived expenses of a student from a certain caste to the expenses faced by students of the same caste.

Even though some scholarships are available, the extent of financial aid for post-secondary education is relatively small. While nationally around 18% of students in post-secondary education get some scholarships, this figure is only around 5% in Jharkhand. In the presence of significant out-of-pocket expenses and variation in costs on account of specific course within track, and institute (e.g. government versus private) attended, a more important source of variation in measured costs is likely on account of the fact that richer students may attend higher quality courses and colleges/institutes.

[11] According to the NSS dataset 18.69% of all students in post-secondary education received some scholarship and 80% of all those who receive scholarships do so on account of their caste status. Around 94% of all scholarships are provided by the government.

Working within the constraint that variables common to both datasets are required to assign measured costs from the NSS data to students in the survey sample, and that these variables explain only around 10-13 percent of the variation in measured costs, I perform the following analysis:

I first estimate, separately for each track j, median out-of-pocket expenses (Y^{MED}_{ijNSS}), that are net of scholarships / stipends / reimbursements received, as a function of k predictors– sex, caste, religion, father's education, mother's education, state of residence, and household occupation[12], with ε_{ijNSS} being error term:

$$Y^{MED}_{ijNSS} = \alpha_{jNSS} + \beta_{1jNSS}X_{1ijNSS}.. + \beta_{kjNSS}X_{kijNSS} + \varepsilon_{ijNSS} \tag{2.8}$$

The parameters $\beta_{1jNSS}..\beta_{kjNSS}$ are then used to predict costs for students in the survey sample:

$$\widehat{Y^{MED}_{ijsurvey}} = \alpha_{jNSS} + \beta_{1jNSS}X_{1ijsurvey}.. + \beta_{kjNSS}X_{kijsurvey} \tag{2.9}$$

Even though expenses faced by students in Jharkhand state likely form the most relevant reference distribution for students in the survey sample, I do not restrict the analysis to Jharkhand specific NSS observations. This is because data on post-

[12]The variable on household occupation differs between the NSS and survey dataset. In the NSS dataset, household occupation is the occupation from which the household derives the majority of its income, in the survey dataset it is the occupation of the father.

secondary attendees from Jharkhand forms less than 2% of the national sample of students in post-secondary education. Given the similarity in the structure of post-secondary education across states and the possibility that students may pursue education out of state, it makes sense to use all observations on post-secondary expenses available. Instead, the coefficient on Jharkhand state is estimated and is used as one explanatory factor in prediction of student-specific measured costs. The remaining parameters are estimated using data for all of India.

2.5 Results

2.5.1 Perceived vs. Measured Expenses: A First Take

Figure 2.2 (technical), Figure 2.3 (general), and Figure 2.4 (vocational), present cumulative distribution function (CDF) plots comparing perceived expenses (from survey sample data) to measured expenses (from NSS data), by post-secondary track. For all three tracks, the perceived expenses distribution (blue) appears to stochastically dominate the measured expenses distribution (red), when we consider NSS data from all of India, with the largest difference in the distributions evident for the general degree track. When restricting the NSS data sample to only post-secondary students in Jharkhand, the dominance of the perceived expenses distribution is unclear for the technical and vocational tracks, though for the general degree track, the dominance of the perceived distribution is starkly evident. At every percentile,

students perceive general degrees to be more expensive than they actually are, irrespective of whether we consider students' expenditures across the country or in Jharkhand state.

Table 2.2 formalizes the difference in perceived and measured distributions using Kolmogorov-Smirnov (K-S) tests. Columns 1-4 test directional hypothesis regarding whether the perceived expenses distribution contains smaller (column 2) or larger (column 4) values than the measured expenses distribution, whereas column 5 tests a combined hypothesis of the maximum difference between the two distributions. When considering the measured earnings averaged nationally, the two distributions are statistically unequal, and the relevant p-values support the directional hypothesis that the perceived expenses distribution contains larger values[13]. When considering measured earnings only for Jharkhand state, the conclusion holds for technical and general tracks, but perceived and measured expenses for the vocational track are statistically identical.

While it does seem to be apparent that in most cases, expenses perceived by students in the survey sample are greater than those actually incurred by students studying in post-secondary tracks, the extent to which these perceived expenses impact perceptions about affordability of a track are unclear. In Table 2.3, I illustrate how perceptions about affordability of a track would change if individuals believed that the median person's expenses applied to them. For this, the fraction of indi-

[13]Directional hypothesis for the technical track are inconclusive, though the largest difference between the two distributions (D-Stat 2) indicates larger values for the perceived distribution.

viduals who perceive each track as affordable is computed, first using data on cost perceptions of students, and then by replacing cost perceptions with the median of measured costs, for each student.[14] I do this for an overall distribution averaged across institute type and separately for expenses incurred by those studying in government and private institutes. While perception about expenses are not collected conditional on institute type, and the survey-sample likely contains a mix of individuals intending to pursue government and private degrees, I perform this exercise to provide an illustrative extreme around the extent of overestimation. In other words, how would affordability of a track change under one extreme assumption of everyone anchoring perceptions on attending government institutes? How would affordability of a track change under the other extreme of everyone anchoring perceptions on attending private institutes?

Change in perceived affordability on account of replacing cost perceptions with median measured costs is the highest for the general track, which would be affordable to 52 percent points more individuals, had individuals perceived their expenses as equal to the median person's. This increase is less dramatic for the vocational track (19 percentage points) and more so for the technical track (6 percentage points) (column 1, Table 2.3). Under the extreme possibility that all students report perceived expenses by anchoring their beliefs on attending private institutes, there is still an increase in affordability when individuals' cost perceptions are replaced with measured expenses of those who attend only private institutes. Affordability for the general

[14] A track is affordable if (max. amount families can pay)-(perceived/measured cost of track) ≥ 0

and vocational track increases by 43 percentage points and 10 percentage points respectively, though the increase in affordability of the technical track is statistically insignificant (column 3, Table 2.3).

I use the median rather than the mean to summarize measured/actual expense distributions, from the NSS data, owing to skewness of the expense distributions to the right. Kernel densities in Figure 2.5-Figure 2.7 show that the median is a better measure of central location of the data.

Section 2.5.3 refines the above analysis in two ways. Currently, it is assumed that all individuals perceive the median person's costs as applicable to them. Doing so disregards the possibility that some people may rationally expect costs to be lower or higher for them, given their personal characteristics. Therefore, the existence of higher values of the perceived distribution relative to the median of the measured distribution, does not immediately lend itself to the possibility that students overestimate education expenses. Therefore, firstly, I attempt to assign to every individual a measured cost, from the NSS data, of a person most similar in "type" to them. In doing so, I also estimate a parameter for state of residence, and assign to all individuals predicted measured costs that are adjusted for their residence in Jharkhand state. Secondly, so far, we have discussed implications of replacing perceived with measured costs for all three tracks in an individual's choice set. I extend this analysis to illustrate implications for an individual's utility maximizing track or the track they would most prefer to pursue. Section 2.5.2 discusses results from estimating the choice model described in section 2.4.1.

2.5.2 Students' Utility Maximizing Tracks

Parameters of the choice-model, resultant from estimating Equation 2.6, are tabled in column 1, Table 2.4. Results from the alternative model in Equation 2.7, are tabled in column 2, Table 2.4. While the qualitative significance of coefficients in Table 2.4 are both hard to interpret (owing to the log-odds specification) and not of central importance in this paper (we are more interested in the distribution of utility maximizing tracks), it is nevertheless useful to provide some interpretation. All three track-specific non-pecuniary beliefs are expressed on a probability scale (0-100). Interpreting coefficients from column 2, Table 2.4, the perceived likelihood of being able to pass all examinations in order to graduate, is not a statistically significant predictor of stated enrollment. Among non-pecuniary factors, parental approval is important–a 10 percentage points increase in the probability of parental approval for a track (relative to non-enrollment) increases the log-odds of stated enrollment by 0.19%, whereas the increase for a commensurate change in perceived enjoyment of coursework is 0.14%. Relative to non-pecuniary beliefs, the beliefs regarding employment probability (also 0-100 scale), bear a still smaller association with intended enrollment. A 10 percentage points increase in the probability of employment for a track (relative to non-enrollment) increases the log-odds of stated enrollment by 0.06%. Individuals are sensitive to expected age-30 earnings: a 1% increase in expected monthly earnings is associated with a 0.9% increase in the log-odds of stated enrollment.

I use the parameter estimates in Table 2.4 to derive the predicted probability of en-

rollment in each track[15] and the utility maximizing track per individual, which is the track with the highest predicted probability of enrollment. These results are reported in Table 2.5. The main difference between the raw stated enrollment probabilities and the predicted enrollment probabilities, is a higher predicted enrollment in the vocational track and lower likelihood of non-enrollment (by 5 percentage points). The difference between the linear mixed model and the quantile regression model is negligible, though I use the utility maximizing tracks predicted by the quantile regression model in further analysis.

2.5.3 Overestimation of Education Expenses: Extent & Implications

2.5.3.1 Prediction of Individual-Specific Costs

Results from estimating Equation 2.8 are presented in Table 2.6. The coefficient values tabled show parameter estimates used to predict relevant measured costs for students in the survey sample. As discussed earlier, in section 2.4.2, variation in measured expenses could arise from several different sources, but we are restricted in this analysis to explain this variation as a function of variables common to both datasets–the survey sample and the NSS dataset. For instance, holding the type of institute and course/degree constant, those belonging to socially disadvantaged castes and poorer families could have fewer out of pocket expenses as compared to

[15] As described in Equation 2.3.

upper caste and richer households, on account of receiving government scholarships and stipends. However, given that the fraction of students receiving scholarships is relatively small, larger out-of-pocket expenses for better off SES groups is likely on account of sorting into better quality institutes and courses/degrees.

Parameter estimates in Table 2.6 are in line with expectation. Relative to males, households of females in all three tracks spend less money on post-secondary education. Relative to the median of each track, females spend between 8.5% (vocational) to 12.5% (technical and general) less money than males per year. While education expenses of scheduled castes (SC) do not statistically differ from those belonging to the scheduled tribe (ST) group, the upper castes spend significantly larger amounts. Relative to STs, the education expenses of those belonging to the "General" caste category are higher by between 25% (technical) and 53% (vocational), relative to median expenses by track. Religion bears no consistent association with education expenses. Children of educated parents spend more, and significant differences in education expenses kick in at lower levels of mothers' education as compared to fathers'. Significant differences in expenses exist between children of fathers with no formal education and children of fathers with post-secondary training. On the other hand, significant differences in expenses exist between children of mothers with no formal schooling and children of mothers with secondary schooling. For instance, relative to children of fathers with no formal schooling, children of fathers with a bachelor's degree spend between 22% (technical) to 47% (vocational) more, relative to median expenses by track.

Relative to farming households, households self-employed in the non-agricultural sector or those with salaried/wage employment do not spend statistically different amounts on post-secondary education. Households engaged in "casual labor in agriculture" spend less money (not statistically significant) as do households engaged in "casual labor in agriculture", relative to farming households. Relative to farming households, households working in "casual labor in agriculture" or agricultural labor households spend between 18.5%-19% less on technical and vocational education, respectively. Finally, the parameters on state of residence are omitted from Table 2.6 but are an important explanatory variable for the prediction of individual-specific costs. Recall from Table 2.1 how median expenses in Jharkhand compare to the all-India average. Out-of-pocket expenses on technical education in Jharkhand are somewhat higher than the all-India average (by 3.6%), expenses on general education are lower (by 15%), and considerably higher for vocational education (by 42%).

These parameter estimates are then used as per Equation 2.9 to predict person-specific costs that serve as a relevant comparison for students perceptions about expenses and guide us in investigating the extent to which students might overestimate post secondary expenses.

2.5.3.2 Overestimation of Education Expenses

In Table 2.7 we examine how perceptions about affordability of a track change when individuals' elicited cost perceptions are replaced with their predicted person-specific

measured costs ($\widehat{Y^{MED}_{ijsurvey}}$), constructed using Equation 2.9. Here, we see a statistically significant increase in affordability of technical tracks, by 10 percentage points, and a large and statistically significant increase in the affordability of general tracks, by 55 percentage points The increase in affordability for the vocational track is small and statistically insignificant. These calculations make it apparent that students' in the survey sample have accurate perceptions about expenses associated with vocational degrees, somewhat overestimate technical degree expenses, and grossly overestimate expenses associated with the general track.

While it is useful to examine separately, for each post-secondary track, students' (mis)perceptions about yearly expenses, it is more insightful to study the extent to which students' misperceive expenses associated with their most preferred track. This is because students may acquire more information about tracks most preferred by them. In Table 2.8 we examine how perceptions about affordability of students' utility maximizing track changes when individuals' elicited cost perceptions are replaced with their predicted person-specific measured costs ($\widehat{Y^{MED}_{ijsurvey}}$). Doing so results in a statistically significant increase of 15 percentage points in students' perceived affordability of the track they would most like to pursue. Almost all of this increase is driven by students' who would most prefer to pursue the general track, though these students form a small subset of the overall pool of students who misperceive general degree costs. Students who would most prefer to pursue the technical and vocational tracks perceive costs associated with these tracks accurately.

2.6 Conclusion

This paper describes the subjective beliefs of a sample of Indian high school students about expenses associated with post-secondary education in the country. The paper describes the extent to which students' seem to overestimate expenses, relative to a reference distribution of students currently attending post-secondary education. Together with data of students' subjective beliefs about their capacity to pay for education, the paper describes the implications of overestimating costs on students' beliefs about their financially feasible choice-sets and affordability of their most preferred track. Students' subjective perceptions about their likelihood of receiving scholarships is also taken into account to compare perceptions about out-of-pocket expenses with out-of-pocket measured expenses.

In my analysis I find that the extent of students' inaccuracy of cost beliefs differs importantly by post-secondary track. More specifically, students make the largest errors for the general degree track, and fail to perceive that these type of degrees are substantially cheaper to enroll in as compared to technical and vocational degrees. I estimate that if students perceived expenses more accurately, then their perceived affordability for technical tracks and general tracks would increase by 10 percentage points and 55 percentage points, respectively, though for vocational tracks students have accurate perceptions about costs at the outset. In addition, I estimate students' utility maximizing tracks using a flexible model of track-choice. I used the methodology proposed by Blass, Lach and Manski (2010) to model stated probabilities, which

is simple to estimate, allows unstructured correlations between alternatives "within" individual and allows individuals to express uncertainty about a decision they will be making in the future. Students have relatively more accurate beliefs about the expenses associated with their most preferred track. If students perceived expenses more accurately, then 15 percentage points more people would believe their utility maximizing track to be affordable to them. To use as reference a measure of actual costs more relevant to an individual than an overall distribution of costs, I assign to every individual a predicted value of measured costs using the set of SES characteristics that overlap both datasets–the survey sample of subjective beliefs and the NSS dataset on measured expenses.

While the paper goes beyond the existing literature in discussing the overestimation of expenses in concurrence with its implications for perceived affordability of education, the main drawback of the analysis is that it stops short of linking perceived unaffordability with real enrollment decisions of students.

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Figures & Tables for Chapter 2

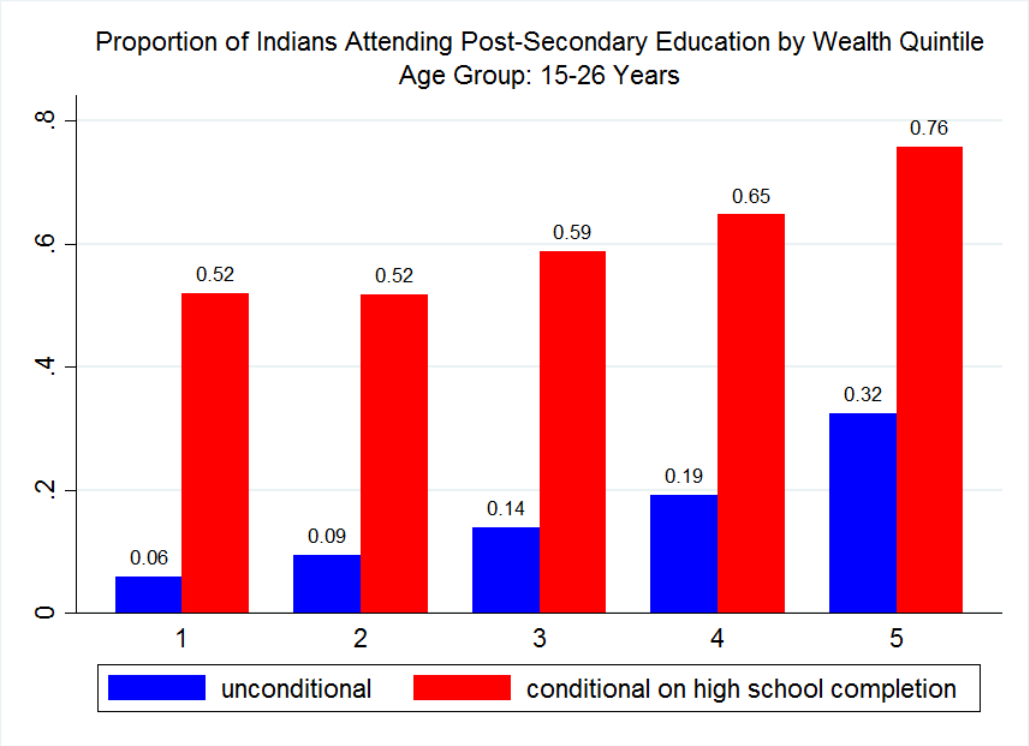

Figure 2.1: Proportion of Indians Attending Post-Secondary Education by Wealth Quintile

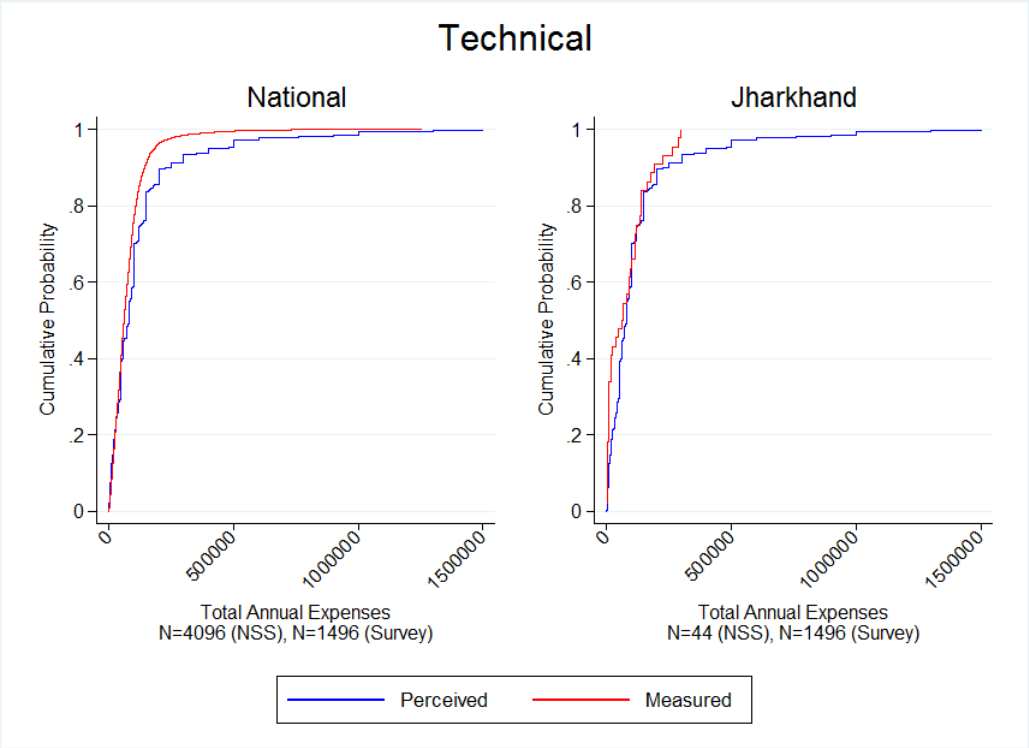

Figure 2.2: CDF Plots of Perceived and Measured Annual Education Expenses using All-India and Jharkhand only NSS data for the Technical track

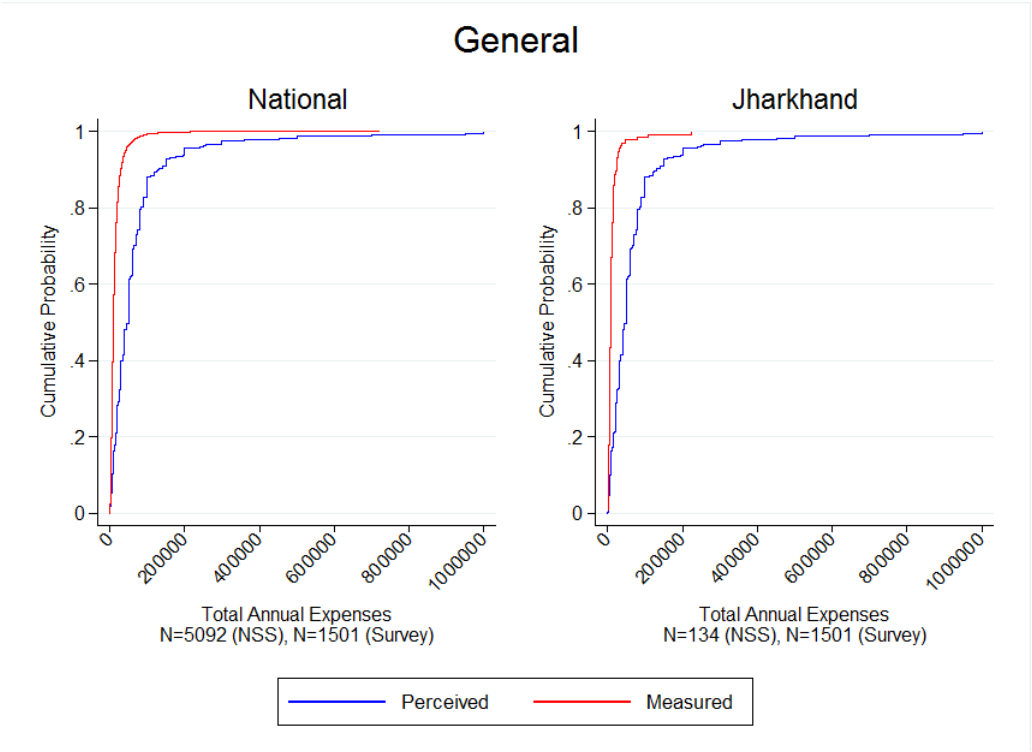

Figure 2.3: CDF Plots of Perceived and Measured Annual Education Expenses using All-India and Jharkhand only NSS data for the General track

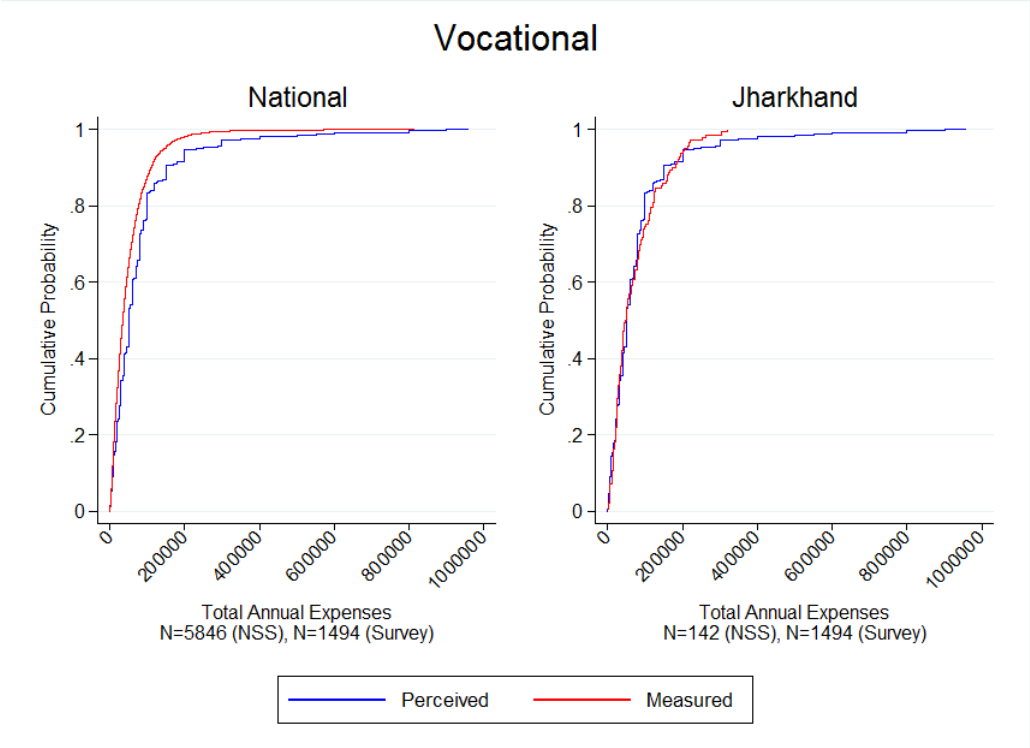

Figure 2.4: CDF Plots of Perceived and Measured Annual Education Expenses using All-India and Jharkhand only NSS data for the Vocational track

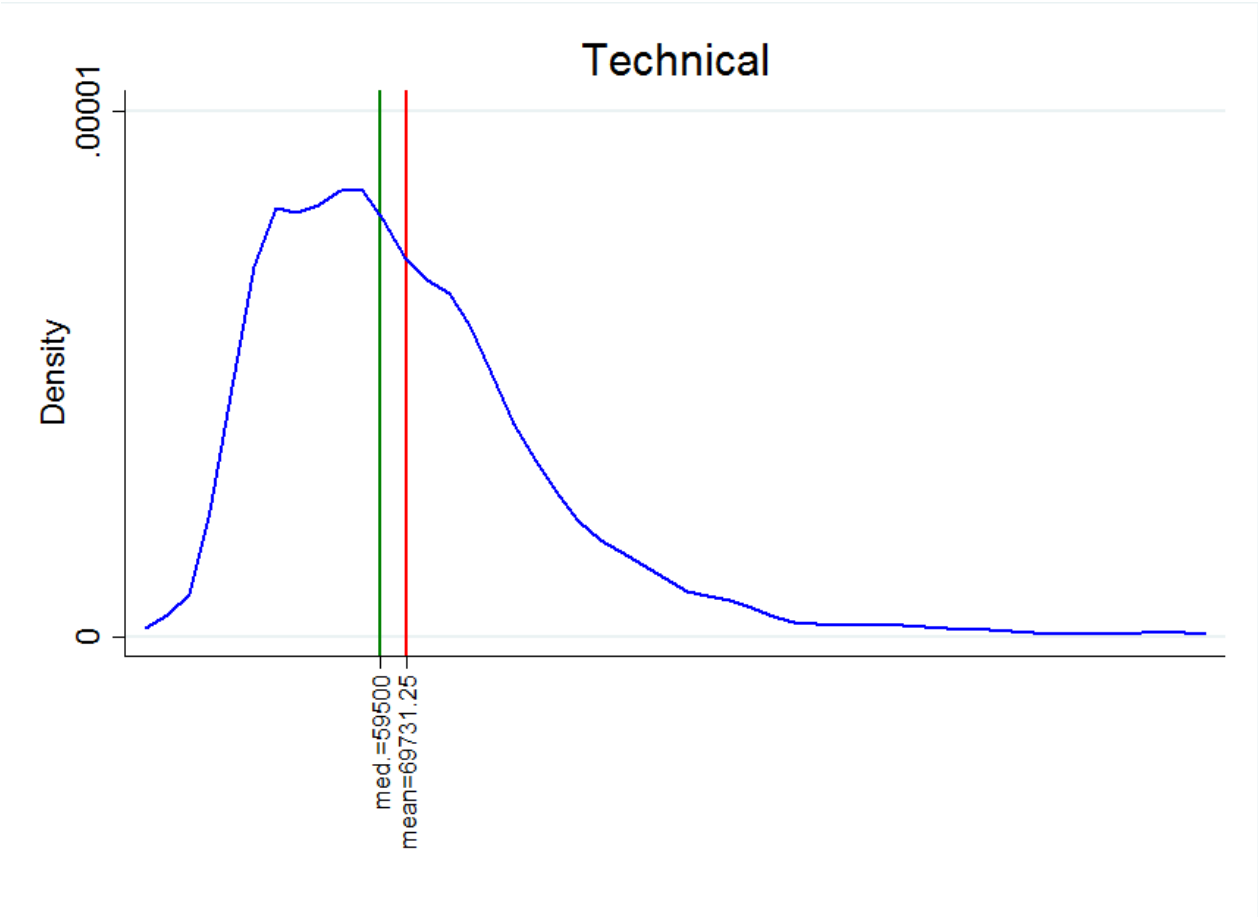

Figure 2.5: Kernel Density of Measured Expenses for Technical Track. Distribution trimmed at 1st and 99th percentile, value of untrimmed mean is Rs. 73,158.41

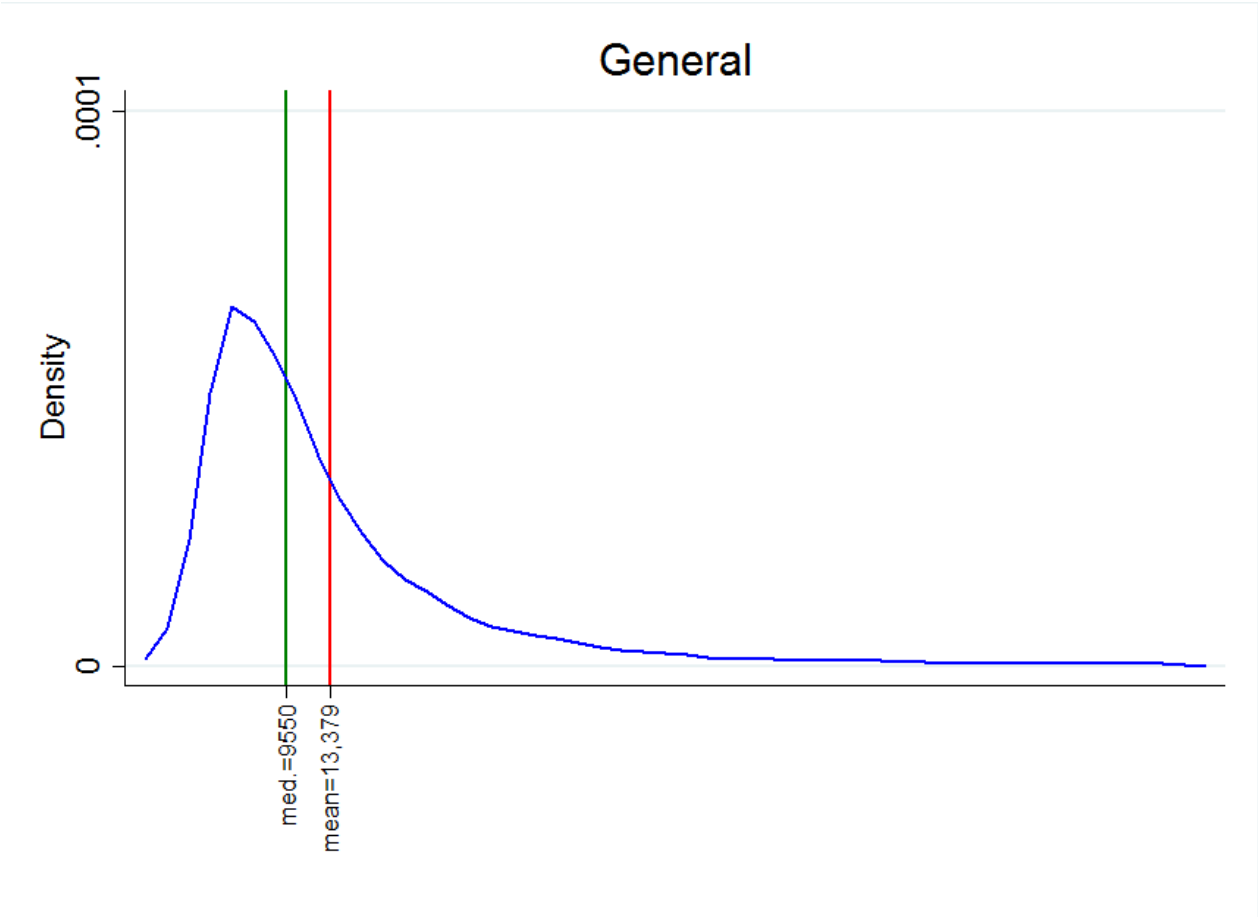

Figure 2.6: Kernel Density of Measured Expenses for General Track. Distribution trimmed at 1st and 99th percentile, value of untrimmed mean is Rs. 14,525.24

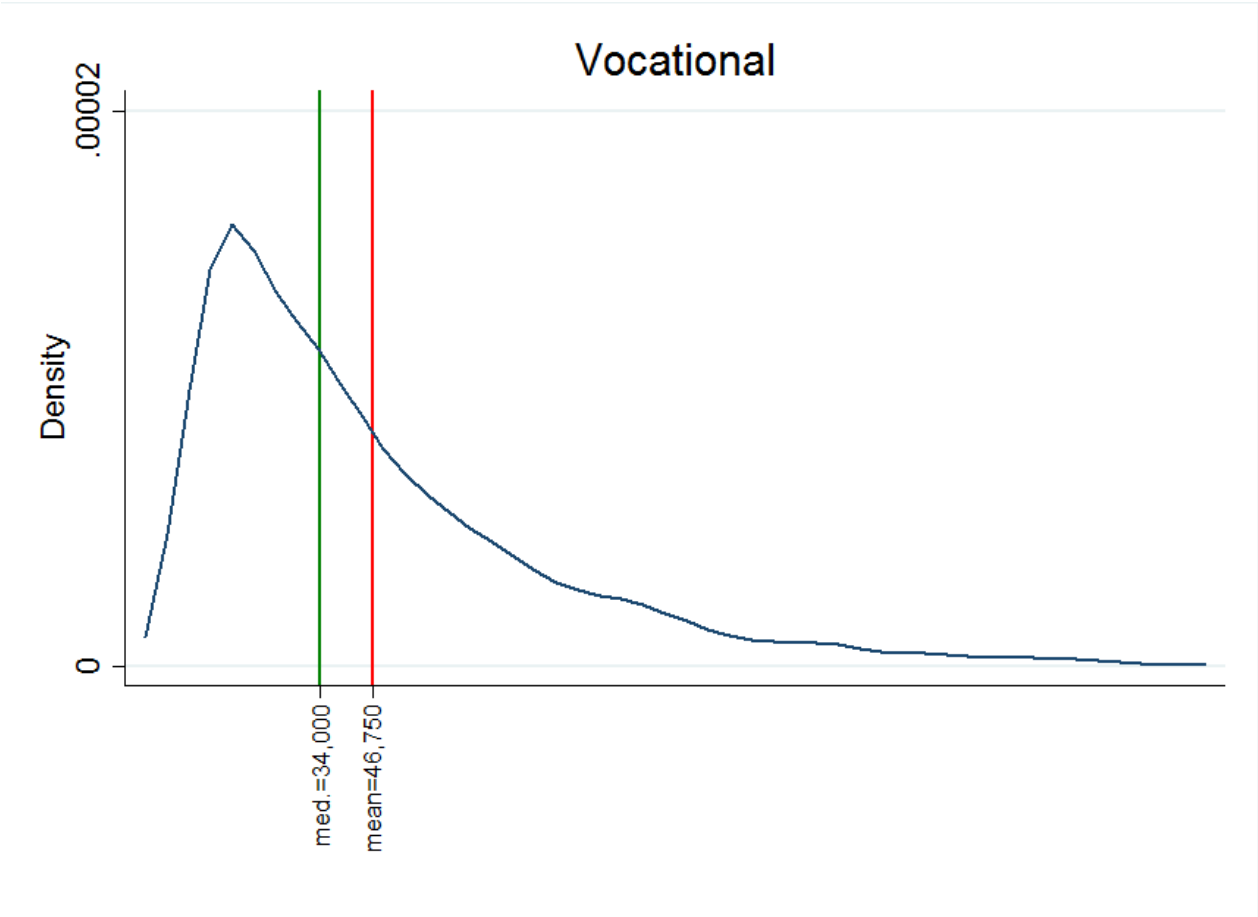

Figure 2.7: Kernel Density of Measured Expenses for Vocational Track. Distribution trimmed at 1st and 99th percentile, value of untrimmed mean is Rs. 49,057.62

Table 2.1: Summary statistics of relevant variables from NSS data

	Technical	General	Vocational
National			
course fee (Rs.)	45,000	3,605	24,000
books, stationery, uniform (Rs.)	5,000	2,000	4,000
transport (Rs.)	3,500	1,500	2,400
private coaching (Rs.)	10,000	5,000	7,500
other expenses (Rs.)	2,000	500	1,200
total expenses (Rs.)	62,315	10,200	36,200
% receive scholarship	19.97%	19.94%	16.54%
amount scholarship received (Rs.)	18,690	3,438	7,000
total expenses net of scholarship (Rs.)	59,500	9,550	34,000
% private institutes	80.63%	49.05%	69.15%
Jharkhand			
course fee (Rs.)	43,800	1,850	34,425
books, stationery, uniform (Rs.)	3,940	1,680	5,550
transport (Rs.)	605	1,440	1,000
private coaching (Rs.)	2,700	3,600	7,200
other expenses (Rs.)	453	450	1,250
total expenses (Rs.)	61,650	8,300	52,985
% receive scholarship	2.27%	5.22%	7.04%
amount scholarship received (Rs.)	14,000	1,200	30,000
total expenses net of scholarship (Rs.)	61,650	8,100	48,575
% private institutes	45.45%	16.54%	71.63%

Notes: (1)Reported expenses are median values for one academic session of 12 months, and for full time courses. (2) 4.8% (national) and 3.6% (Jharkhand) of students receive some tuition fee waivers, the course fee reported is for expenses actually incurred. (3) 6.09% (national) and 3.75% (Jharkhand) of students receive subsidies for textbooks, the books fee reported refers to actual expenses incurred.

Table 2.2: Testing for Equality of Perceived & Measured Expenses Distributions using Kolmogorov-Smirnov Tests

	(1) D-stat 1	(2) P-value (col 1)	(3) D-stat 2	(4) P-value (col 3)	(5) P-value (comb.)
National					
Technical	0.0539	0.002	-0.1707	0.000	0.000
General	0.0011	0.997	-0.588	0.000	0.000
Vocational	0.0142	0.621	-0.2091	0.000	0.000
Jharkhand					
Technical	0.0642	0.703	-0.243	0.006	0.008
General	0.0133	0.957	-0.6762	0.000	0.000
Vocational	0.0869	0.141	-0.0819	0.176	0.246

Notes: (1) tests the hypothesis that "perceived" expense distribution contains smaller values than "measured" expense distribution. (2) tests the hypothesis that "perceived" expense distribution contains larger values than the "measured" expense distribution. P-value for the combined hypothesis tests for the max. of the two directional hypothesis. Obs. in the NSS data for all-India: 4096 (tech.), 5902 (gen.), 5846 (voc.). Obs. in the NSS data for Jharkhand: 44 (tech.), 134 (gen.) & 142 (voc.). Approx. 1500 obs. in Survey dataset for all 3 tracks.

Table 2.3: Change in Track-wise Affordability (when perceived expenses are replaced with median of measured expenses)

	National	Government	Private
% of individuals who can afford each track based on cost perceptions (SE)			
Technical	0.18 (0.010)	0.18 (0.010)	0.18 (0.010)
General	0.32 (0.012)	0.32 (0.012)	0.32 (0.012)
Vocational	0.28 (0.012)	0.28 (0.012)	0.28 (0.012)
% of individuals who can afford each track based on measured costs (SE)			
Technical	0.24 (0.011)	0.47 (0.01)	0.20 (0.010)
General	0.83 (0.01)	0.85 (0.009)	0.74 (0.011)
Vocational	0.47 (0.013)	0.70 (0.012)	0.38 (0.012)
Change (95% CI)			
Technical	0.06 (0.03-0.09)	0.29 (0.26-0.32)	0.02 (-0.01-0.04)
General	0.52 (0.49-0.55)	0.53 (0.50-0.56)	0.43 (0.40-0.46)
Vocational	0.19 (0.15-0.22)	0.42 (0.38-0.45)	0.10 (0.07-0.13)

Table 2.4: Parameter estimates of Track-Choice Model

	(1) Linear Mixed	(2) Quantile
enjoy coursework	0.0173***	0.0137***
	(0.000903)	(0.00134)
pass prob.	0.00596***	0.00226
	(0.00102)	(0.00147)
parental approval	0.0125***	0.0188***
	(0.000776)	(0.000876)
employment probability	0.00466***	0.00628***
	(0.00104)	(0.00125)
log wages	0.0605**	0.0883***
	(0.0271)	(0.0331)
Constant	-0.812	-1.079
	(1.290)	(1.056)
Observations	4,560	4,560
R-squared	0.230	0.187

Notes: Robust standard errors in parentheses.*** p<0.01, **p<0.05,* p<0.1. Controls for age, sex, caste, religion, college & stream are added for all regressions.

Table 2.5: Predicted Enrollment Probabilities & Distribution of Utility Maximizing Tracks

	Predicted Enrollment Probability			Utility Max. Tracks		
	Raw Data	Linear Mixed	Quantile	Raw Data	Linear Mixed	Quantile
Technical	0.361	0.360	0.373	0.404	0.406	0.410
General	0.325	0.322	0.319	0.322	0.315	0.299
Vocational	0.233	0.285	0.281	0.212	0.274	0.277
Not Enroll	0.081	0.033	0.027	0.062	0.005	0.014

Table 2.6: Parameters of SES Variables that Explain Variation in Measured Costs

	(1) Technical	(2) General	(3) Vocational
Sex			
Female	-7,474***	-1,211***	-2,901*
Caste			
Scheduled Caste	-2,352	1,046	5,109
Other Backward Caste	5,571	2,374***	11,504***
General/Other	15,059***	3,769***	18,154***
Religion			
Islam	-1,234	-628.4	499.1
Christianity	19,559***	741.8	-1,626
Sikhism	-6,047	3,320**	3,586
Jainism	-3,817	1,666	-6,004
Buddhism	-20,437	-514.8	-1,236
Zoroastrianism	11,705	98,262***	-4,569
Other	29,067	-1,802	13,598
Father's Education			
Primary & below	4,254	166.4	-810.7
Middle	-1,525	1,026	2,593
Secondary	3,106	1,898***	6,435**
Higher Secondary	7,700	870.6	7,654**
Vocational Diploma	11,140	3,290***	19,501***
Bachelor's	13,088**	2,265***	16,027***
Post graduate & above	26,969***	2,248**	32,613***
Mother's Education			
Primary & below	5,232	-210.1	758.2
Middle	7,144*	678.8	4,288*
Secondary	10,788***	1,810***	5,834**
Higher Secondary	11,376**	1,735**	10,412***
Vocational Diploma	27,209***	6,085***	21,457***
Bachelor's	22,082***	5,458***	14,690***
Post graduate & above	17,399**	8,622***	13,648**
Household Occupation			
Self-employed in Non-Ag.	1,142	296.4	-1,534
Regular wage/Salaried job	985.9	948.5**	896.9
Casual labor in Ag.	-9,851	-1,131	-5,060
Casual labor in Non-Ag.	-11,363**	-396.8	-6,276**
Constant	49,893***	7,351***	16,851***
Observations	3,112	4,261	4,313
Median	59,500	9,550	34,000
Pseudo R2	0.135	0.102	0.105

Note: State of residence is also controlled for, omitted for brevity. Standard errors in parentheses.*** p<0.01,** p<0.05,*p<0.1. The base categories are Male, ST, Hinduism, No Formal Schooling & Self-Employed in Ag.

Table 2.7: Change in Track-wise Affordability
(Median regression used for predicting person-specific measured costs)

	Proportion	**Standard Error**	
% of individuals who can afford each based on cost-perceptions			
Technical	0.18	0.011	
General	0.32	0.013	
Vocational	0.29	0.013	
% of individuals who can afford each track based on measured costs			
Technical	0.28	0.013	
General	0.87	0.010	
Vocational	0.32	0.013	
Change		**95% CI**	
Technical	0.10	0.06	0.13
General	0.55	0.51	0.58
Vocational	0.04	0.00	0.07

Table 2.8: Percentage-Point Change in Affordability of Utility Maximizing Track
(Median regression used for predicting person-specific measured costs)

	Proportion	**Standard Error**	
% of individuals who can afford utility max. track			
Based on cost-perceptions	0.33	0.013	
Based on measured costs	0.47	0.014	
		95% CI	
Percentage-point change	0.15	0.11	0.18
Break-Down of Change by Track			
Technical	0.010		
General	0.140		
Vocational	-0.003		

CHAPTER 3

THE ROLE OF AGRICULTURE IN WOMEN'S NUTRITION: EMPIRICAL EVIDENCE FROM INDIA

3.1 Introduction

Low body-mass index (BMI) among women of childbearing age (15-49 years), indicative of maternal undernutrition, is a grave public health concern because its implications extend well beyond the individual herself. Maternal undernutrition contributes to fetal growth restriction, which increases the risk of neonatal deaths and, for surviving children, of stunting (Black et al. (2013)). Indian women are particularly at risk of being too thin. Adjusting for the characteristics[1] of pregnant women, it is estimated that approximately 42.2% of pre-pregnant women in India are underweight (Coffey (2015)). In yet another stark manifestation of the Asian Enigma (Vulimiri, Urban and Jon (1996)), in Sub-Saharan Africa, only 16.5% of pre-pregnant women are estimated to be underweight, even though they are much poorer.

Among the reasons advanced for the poor nutritional status of Indian women, an enduring explanation relates to the intra-household status of women. Several indicators of womens status in the literature consistently rank women in the countries of South Asia as lower in comparison to their counterparts in Asia, Africa, Latin America

[1]In India, fertility is concentrated among women in their early twenties as opposed to Sub-Saharan Africa where childbearing is more spread out between the ages of 17-35 years. Indian women in their early twenties are almost 15 pp. more likely to be underweight than 40 year old women (Coffey (2015)).

and the Caribbean (Haddad (1999)). The Indian case is particularly unique whereby features of familial structure and cultural norms that designate inter-personal hierarchies foster low social-status among women with perpetuating consequences for her own and her childs health (Coffey, Khera and Spears (2013)). Worryingly, recent numbers emerging from the Rapid Survey on Children (RSOC) conducted by the Union Ministry of Women and Child Development and UNICEF[2] show that while India has seen encouraging progress on metrics of child malnutrition since 2005, the situation for adolescent girls aged 15-19 years has barely budged with close to 45% of girls in the age-group having BMI of less than 18.5. With this context in mind, policy interventions that have the potential to increase the bargaining power of women, hold particular promise in addressing the problem of maternal malnutrition in the country.

Recent, academic and policy interest in leveraging the agricultural sector in developing countries to combat the scourge of malnutrition, is motivated, in part, by the fact that agriculture is not only a major employer overall in these countries, but is a major employer of women in particular (Harris, Kadiyala et al. (2012), Pingali, Ricketts and Sahn (2015), Ruel et al. (2013)). Therefore, one important pathway by which agriculture is linked to nutrition is by way of being a source of income for women, which in turn can influence the intra-household allocation of food and other nutrition-enhancing complements (Hoddinott and Haddad (1995), Bobonis (2009)). At the same time, heavy agricultural workloads and exposure to toxins and disease

[2]Rapid Survey on Children (provisional report) by the Ministry of Women and Child Development and the UNICEF accessed on 12.12.2015 from http://wcd.nic.in/issnip/National_Fact%20sheet_RSOC%20_02-07-2015.pdf.

through agricultural activities can deleteriously affect women's health and nutrition and also have negative consequences for lactation and child-care (Jones et al. (2012),Hoddinott (2012)). Therefore, the net implications of agricultural work for womens nutrition require empirical investigation. Other pathways by which agriculture and nutrition are posited to be linked include, production for own-consumption (particularly relevant in the face of high transaction costs and missing markets for nutritious foods), overall income effects for net-sellers of food and price-effects for net-buyers (Kadiyala et al. (2014), Carletto et al. (2015)).

In a narrative synthesis of the existing malnutrition literature in India (Pingali and Rao (2017)), find less than ten papers in peer-reviewed journals that empirically examine different determinants of women's nutrition, as measured by anthropometric outcomes (also see (Kadiyala et al. (2014)) for a related and relevant review). Moreover, all of these studies use cross-sectional data, and most of them do not extensively control for confounding effects. Therefore, while the potential of the agricultural sector to address problems of malnutrition is promising, at the household-level, there is little empirical evidence for whether income growth in agriculture is particularly beneficial for improved nutritional outcomes and in particular, anthropometrics. One constraint in the Indian context is the availability of anthropometric data, which is strikingly lacking. Periodic National Family and Health Surveys (NFHS) which collect nationally representative anthropometric data on children and adults, do not collect detailed income and agriculture data and, moreover, havent released any unit data in over a decade[3]. In this paper, we respond to this gap, by using five years

[3]The NFHS-4 released aggregated health reports for 13 states in 2015-16. However, the survey

of household-level panel data, from 18 villages across 5 Indian states, collected by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) as part of the Village Dynamics in South Asia (VDSA) program, to establish the link between household agricultural income and womens nutritional status, and explore the pathways by which agricultural incomes may affect nutrition.

Some existing findings, on agricultural output and malnutrition, in the literature provide context and aid in the interpretation of our results. The effect of agricultural production on malnutrition at the state-level is inconclusive in the Indian context. For instance, (Gulati et al. (2012)) find a modest effect of state-level agricultural production on both child and adult malnutrition metrics but use cross-sectional data with few controls. On the other hand, (Headey (2013)), finds the effect of state level agricultural growth on childhood stunting, with state fixed effects, to be particularly weak for Indian states. In a household fixed-effects study, using Tanzanian data, (Slavchevska (2015)), establishes a statistically important, positive (inelastic) effect of household harvest value of crops on height-for-age z-scores of children under 5. However, the author does not find any effects of the same for adults. Partly, this could be because, adult underweight is not a substantial problem in their context, with only about 9 percent of the adult sample being underweight. Using methods comparable to ours and of (Slavchevska (2015)), (Kirk et al. (2015)) use three years of data to examine effects of sector-specific incomes in Uganda. They do not find agricultural incomes to play a crucial role in improving measures of child malnutrition, but caution that their results are heavily context specific to the agricultural

is still in the field for the remaining states and unit data for all states is yet to be released.

and dietary profile of Uganda.

Some recent studies also throw light on specific pathways by which agriculture may affect nutrition. For instance, (Hirvonen and Hoddinott (2016)), find that there is a link between household-level production diversity and diversity of diets among pre-school children in rural Ethiopia, but it breaks down for households that have market access to food. The potential of two agricultural pathways, production for own-consumption (measured by production diversity) and income effects (measured by agricultural revenue), on household dietary diversity has been looked at in the Nigerian context (Dillon, McGee and Oseni (2015)). The authors find both pathways to have statistically significant but relatively inelastic effects on household dietary diversity. Our findings strengthen the existing literature in multiple ways. Firstly, we show that there is a statistically significant relationship between household agricultural income and individual nutrition. We do so, both, by utilizing within household, year to year, variation in household agricultural income and by associating growth in agricultural income with growth in BMI over the longer term. Here, we contribute to the limited pool of estimates, across countries, which provide a measure for the agricultural income elasticity of anthropometrics. Further, we establish that production for self-consumption plays only a limited role in producing nutritional improvements in our data, but the role of food purchases and hence household income is important. Finally, we establish heterogeneous effects by women's age and show significantly higher impact of agricultural income on the nutritional status of younger women.

3.2 Data & Summary Statistics

This paper uses five years (2009-2013) of publicly available household and individual level panel data collected by ICRISAT as part of the VDSA program. The data are drawn from 18 villages across 5 Indian states Andhra Pradesh/Telangana, Gujarat, Karnataka, Maharashtra and Madhya Pradesh. The total number of individuals with valid BMI data in the sample varies from year to year; and ranges between 791-992 individuals. Rainfall data is from the University of Delaware Air Temperature and Precipitation database.

Table 3.1 lists the key variables we use in our analysis along with their means and standard deviations. Anthropometric data is collected annually, at the beginning of the survey cycle, and income and consumption data are collected monthly, in subsequent months. In view of this feature of the survey design, we lag all our explanatory variable by a year, to predict the following years BMI, our outcome variable of interest. Thus, BMI data used in the study applies to years 2010-2013[4] and data from 2009-2012 are used for the explanatory variables. This ensures that BMI data in every year is measured after income and expenditure data for the year. Figure 3.1 plots the cross-sectional distribution of the BMI of sample women[5]. Among all

[4]Anthropometric data collection in VDSA villages, from the five states, started in 2010.

[5]BMI data that is likely measurement error is excluded from the analysis. For all individuals having BMI less than 11 and greater than 40, and for individuals with individual-level BMI deviations smaller than the 1st percentile and larger than the 99th percentile, we consider observations of the individual for all years, on a case-by-case basis, to classify the BMI observation as measurement error or not. This is done, primarily, based on consistency of height values recorded in other years for the individual. In all, only 0.42% of all BMI observations are excluded on account of being measurement error.

women of child-bearing age, between 15-49 years, 33% of women are underweight with BMI<18.5. This number is worryingly high, and shows little progress since the DHS national average of 35% underweight women in 2005. Moreover, the incidence of underweight for younger women (15-25 y), among whom fertility is primarily concentrated, is higher by more than 13 percentage points, with the BMI distribution for this age-group having a larger mass of observations in the low BMI ranges. Figure 3.2 plots the distribution of the deviations of women's year-specific BMI from their mean BMI. As is to be expected, within-individual variation in BMI, which we will be utilizing for our panel data analysis, is more limited, but nevertheless sufficient to yield meaningful insights. The average yearly deviation from individual-specific BMI means is 0.65 points and for 95 percent of the women in our sample BMI varies within a band of +/- 2 BMI points. Even though we explicitly check for and exclude BMI observations that are undoubtedly measurement-error (primarily based on older individuals for whom a lower height was recorded in a subsequent year), there are some still observations with large absolute deviations in BMI, owing to wide fluctuations in the weight of the individual over the span of four-years. We examine how our results are affected by the presence of such outlier individuals in subsequent analysis.

3.3 Empirical Specification

We set-up our econometric framework to (a) quantify the effect of agricultural income on womens BMI over the short-term by modelling year-wise deviations in BMI from person-specific means as a function of deviations in household agricultural income; (b) estimate the growth in womens BMI, over a span of four years, as a function of the growth in her households agricultural income. The growth specification averages out positive and negative yearly fluctuations in income and helps to estimate the cumulative effect of income from agriculture, over time. We examine the effect of agricultural income on individual nutritional status over the short-term (one year) using the regression specification in (Equation 3.1):

$$BMI_{ihvt} = \alpha_{ihvt} + \beta_1 f(GVA_{hvt}) + \beta_2 A_{hvt} + \beta_3 P_{hvt} + \beta_4 X_{hvt} + \gamma_{ih} + \varepsilon_{ihvt} \tag{3.1}$$

As an indicator of individual nutritional status, we are interested in the BMI of women of child-bearing age, which is measured as a continuous variable. As our measure of agricultural income, we are interested in the effect of "Gross Value Added (GVA)" per acre which is measured, at the household level, in monetary terms using household-level sale prices of crop output. The function $f(.)$ is an inverse hyperbolic sine (IHS), a transformation which works akin to a log transformation in terms of reducing the weight attached to extreme observations, but is defined for zero-

valued observations (Burbidge, Magee and Robb (1988))[6]. A_{hvt} is total area in acres cultivated by a household in year t, an important control-variable which intends to capture productivity differentials on account of land-size (Barrett (1996)) which also likely correlate with nutritional differences across households and within individuals over time. We model participation in agriculture in a given year by including a participation dummy with $P_{hvt} = 0$ if $GVA_{hvt} = 0$ and $P_{hvt} = 1$ if $GVA_{hvt} > 0$. α_{ihvt} is the constant and ε_{ihvt} is the mean zero error term.

The inclusion of individual level fixed effects (γ_{ih}) differences out time-invariant individual-level factors which could potentially confound the effect of GVA_{hvt} on BMI_{ihvt}. Identification of the effect of GVA_{hvt} on BMI_{ihvt} rests on the identifying assumption that time variant heterogeneity between individuals does not bias β_1 on account of inducing correlation between GVA_{hvt} and ε_{ihvt}. Given our data, this assumption is not directly verifiable. Next best, we sequentially control for the most likely time-variant factors that could potentially account for the apparent relationship between GVA_{hvt} and BMI_{ihvt} and do not find them to substantially alter our relationship of interest. In a separate specification (Equation 3.2), described below, we also estimate the long term growth (over four years) of women's BMI as a function of the growth of her household's agricultural income, controlling for growth in other relevant dimensions, and find statistical support for our hypothesis. This specification, which averages out year-to-year fluctuations in BMI and GVA, is less likely to be susceptible to unobserved year-specific shocks. Taken together, both sets

[6]Nevertheless, results are nearly identical when the transformation $g(GVA) = ln(GVA + 1)$ is used, and are available upon request.

of results lend credibility to our identifying assumption.

We estimate the effect of agricultural income growth on BMI growth, over the long term as per the time-period of this study using:

$$g_{ihv}^{BMI} = \alpha_{ihv} + \beta_1 g_{hv}^{GVA} + \beta_2 g_{hv}^{A} + \beta_3 g_{hv}^{X} + \varepsilon_{ihv} \tag{3.2}$$

Where, g_{ihv}^{BMI} is the growth rate of women-specific BMI, g_{hv}^{GVA} is growth rate of household GVA/acre, g_{hv}^{A} is the growth rate of cultivated area and g_{hv}^{X} is the growth rate of control variables. The growth rate of each included variable (measured at either the individual or household level) is calculated by estimating (Equation 3.3) for every individual in the sample and capturing the coefficient on year (t)[7]:

$$ln(Y_{ih}) = ln(\alpha_{ih}) + g_{ih}t + ln(\varepsilon_{ih}) \tag{3.3}$$

Included time-variant controls (X_{ihvt}) in (Equation 3.1) and g_{hv}^{X} in (Equation 3.2) include changes in family size, changing access to amenities critical to both agricultural income and nutrition (household level access to electricity and piped water/water from a drinking water well), non-agricultural sources of household income, house-

[7]Equation (3.3) results from taking logs of the non-linear "exponential growth" equation $Y = \alpha(e)^{gt}\varepsilon$. Notice that this specification also implicitly accounts for an individual fixed-effect (for variables measured at the individual level) and household fixed-effect (for household level variables). Say, c denotes a fixed effect, and $Y = \alpha(e)^{gt}\varepsilon c$. Taking logs on both sides drops out the fixed effect (a dummy variable taking value of 1 for the relevant household) and we are back to estimating (3.3).

hold medical expenditure and village-level rainfall. One of the major strengths of the ICRISAT data are the detailed manner in which household income is tracked- not based on recall as is typical in surveys of this kind, but through monthly visitations to households. We include four major categories of non-agricultural income as controls- livestock income, income from non-agriculture, unearned income and income from agriculture labor[8]. In the absence of detailed health data, household medical expenditure is used as a proxy for year-specific health shocks which could both effect agricultural income through the capacity to work on farm and directly affect BMI. Village-level rainfall, undoubtedly affects agricultural productivity and also likely affects nutrition outcomes via altering the individuals disease environment[9].

Finally, to account for unobserved aggregate shocks, we cluster our standard errors

[8]Income from non-agriculture includes income from salaried jobs, income from caste occupations, business income, other non-farm income and income from non-farm migratory work. Unearned income includes gifts and remittances, savings and deposits and rental income. Agricultural labor income includes income from both working in the village labor market and migratory labor income.

[9]A different strategy to address concerns of correlation between GVA_{hvt} and ε_{ihvt} would be to instrument GVA_{hvt} with a variable correlated with agricultural income but not with individual nutrition. However, our dataset does not offer suitable instruments to pursue this strategy. Both soil quality and irrigation, instruments suggested in the literature (Slavchevska (2015)) to address endogeneity concerns, lack within individual variation over time, necessary for identification in our model. For instance, the median yearly deviation of "cultivated area under irrigation", from individual-specific means is 0. Another identification concern relevant in this context is one of reverse causality. This is the idea that better nourished individuals may be able to apply their labor more intensively in the agricultural production process and may hence enjoy higher output. Even though, clearly, BMI in our data is recorded after data on agricultural output for a year was collected, temporal persistence in BMI data could potentially invalidate our results. To check whether this is a concern in our context, we include lagged BMI (by a year) in our final specification as an explanatory variable. The inclusion of lagged BMI, has no effect on the estimated effect size of GVA_{hvt}, in fact the effect is somewhat strengthened. However, by including lagged BMI we lose close to 40 percent of our observations, which nearly doubles our standard errors, making our inference imprecise. Since anthropometric data collection started only in 2010, by including in lagged BMI, we lose all of our 2010 observations (BMI missing for 2009) and some additional observations for which BMI in the previous year was missing. These results have been omitted for brevity but are available upon request.

at the village level. Because we have a small number of villages (n=18), we bootstrap standard errors on our coefficients of interest using Wild cluster bootstrapping (Cameron and Miller (2015)). This addresses concerns that with a small number of clusters standard asymptotic theory cannot be used to make inference and the use of standard distributional assumptions yield confidence intervals that are "too narrow". To address concerns regarding serially correlated errors, we also alternatively cluster at the individual level, but in most cases these standard errors are smaller and therefore have been omitted for the sake of brevity, but are available upon request.

3.4 Results

3.4.1 Do Agricultural Incomes Impact Womens Nutritional Status?

The extent to which the agricultural sector can influence individuals' nutritional status, is a function of the size of the sector and its economic importance at the household-level. In the context of diversifying rural economic activity and the growing importance of the rural non-farm sector, the role of agriculture in poverty reduction and nutritional improvements, is not immediately obvious and requires detailed consideration. In Figure 3.3 we look at the sectoral composition of household incomes, to investigate the relative economic significance of farming activity. Income from farming (i.e. crop income) is the largest source of income for households in

our sample and, on average, accounts for around a third of all income. In comparison, the share of earned non-agricultural income, while on an upward trend, is still small, relative to farming. The "unearned income category comprises of rental income (including rent from land), income from gifts and remittances and savings and deposits.

Thus, the break-down of the sectoral composition of household incomes posits an important role of crop incomes as a source of income for purchases and production of food for self-consumption. We also find descriptive evidence to support that the relative efficacy of crop incomes versus non-agricultural incomes, in improving nutrition, could be operating via the gender pathway. Across both the non-agricultural sector and farming, a majority of income earned accrues to males. However, as can be seen in Figure 3.4, the proportion of income accruing to women, is nearly two times as large in farming as it is in non-agriculture. To the extent that women spend more time working in farming than in non-agriculture, increases in agricultural output can plausibly afford women control over a larger share of household economic production and hence greater bargaining power over the allocation of household resources.

Table 3.2 presents results, from our baseline specification (without secondary controls), of the effect of agricultural income on womens BMI. For single crop estimates, "yield" (i.e. quantity of output per acre) is often used as a simple measure of output. GVA is a comparable measure, except it is in monetary terms and allows us to aggregate across crops. Aggregation across crops is necessary in our sample because of the wide variety of crops that households grow. Column (1) includes village fixed

effects and column (2) includes individual fixed effects. Therefore, in column (1), we compare women's BMI across households with differing agricultural incomes, within village and year. These estimates utilize cross-sectional variation across households and compared to the estimates in column (2) are demonstrably biased upwards. In column (2), we estimate individual-level deviations in BMI (from their person-specific means) as a function of year-wise deviations in household GVA/acre and, hence, utilize within-individual variation in estimating the effect of agricultural incomes. These estimates are not confounded by observed and unobserved time-invariant differences between individuals that weaken the validity of cross-sectional estimates.

In Figure 3.2 we see some individuals with very large BMI changes (<-4/>+4) over the time-period under consideration. Heights for these individuals were indeed recorded consistently, and large BMI changes are purely attributable to large changes in weight, a metric for which it is considerably harder to discern between actual changes versus measurement error. In column (3), we explore how sensitive our estimates are to the exclusion of outliers. In particular, we exclude 15 smallest and 15 largest individual-level BMI deviations to find that the point estimate on GVA/acre reduces somewhat. The results however become more precise. In a subsequent section, we analyze the implications of our findings for the range of effect-sizes implied by our treatment of outlier observations. In Table 3.2 and in subsequent tables, for robustness, we present results first with no outliers dropped and next with 15 smallest and 15 largest observations dropped[10].

[10]To justify why we exclude 15 smallest and 15 largest observations, in Table 3.3 we report how the effect-size changes when 5, 10 and 15 smallest and largest observations are dropped from the sample. Dropping the 5 smallest and 5 largest observations has the largest impact on our estimate

Cross-sectional/within village estimates are presented in Table 3.4 for comparison with subsequent results that include individual fixed effects (Table 3.5). From the cross-sectional results in Table 3.4 it is apparent that once we account for other differences between households and individuals by including relevant controls, no independent statistically significant effect of agricultural income on BMI can be established. Table 3.5 presents results from the short term specification (Equation 1) and sequentially adds in household-level controls (col. 1), village-level rainfall (col. 2), removes BMI outliers (col. 3), and presents a final set of results with the full set of controls and without outliers (col. 4). Here, once we account for individual fixed effects, the effect of agricultural income on women's BMI is robust to the inclusion of household level controls shown in column (1). This points to the importance of household and individual level panel data in establishing the result on the effect of agricultural income on nutritional status. In column (2), we control for village-level annual rainfall, which only somewhat moderates the effect of GVA/acre on BMI. Dropping the 15 smallest and 15 largest BMI changes, results in a somewhat smaller but more precise effect-size (columns 3 & 4).

The sign of the coefficient on household level access to electricity in columns (3,4) is not in line with intuition. However, given high average levels of electrification in the sample villages (93-96 percent in 2010-2013), it is possible that households electrified during the time-period in our study, that is households electrified last,

of GVA/acre (point estimate drops by around 19 percent), but dropping subsequent observations have a much smaller impact on our point estimate of interest. Moreover, after dropping 15 smallest and 15 largest observations, the next 5 observations on either tail range from 10-14 kilos of weight change over the time period in our sample, which are plausible weight changes, especially considering that given that our panel is not a balanced one.

were the worst off households where no year-on-year improvements in maternal BMI were seen. Nevertheless, as a first order concern, electricity at the household level is not correlated with household agricultural output, which is re-assuring. Notice, that in all specifications the sign on the coefficient on the indicator for agricultural sector participation is consistently negative. Therefore, households that farm have, on average, lower BMI than households that do not, which could partly indicate high energy expenditure on account of agricultural work. Thus, the positive sign on agricultural income is conditional on agricultural-sector participation, with 77 percent of the sample households participating in the sector.

One concern may be that the income variables included are not statistically significant and hence may not be serving as effective controls on account of being insufficiently correlated with BMI. In Table 3.6, we re-estimate Table 3.5 with the four non-agricultural income variables being included as quartiles. As can be seen, higher quartiles of non-agricultural income, unearned income and agricultural labor income are indeed significantly correlated with better BMI outcomes. However, accounting for these controls does not substantially alter the effect of GVA/acre.

The linear-log relationship between BMI and household agricultural income, as modeled in Equation 1 implies a 10 percent increase in GVA/acre is associated with a BMI increase of 0.0088-0.0117 points, which is a 0.04-0.06 percent increase relative to mean BMI. To further give a sense of the economic implication of our results, we use the parameter-estimate obtained on the GVA/acre coefficient from different specifications of our individual fixed-effects model, to compare predicted BMI at

specific levels of agricultural income. Using the parameter estimates from Table 3.5, column (2), we find that the difference in predicted BMI between households with no crop income and households at the median level of agricultural income is 1.05 BMI points. Relatedly, predicted BMI increases by 0.29 points when individuals between the 25th and the 75th percentile of the GVA/acre distribution are compared, with all other variables in the concerned regression, being held at their mean values. When parameter estimates from columns (3) and (4) of Table 3.5 are used, we find that predicted BMI increases by 0.27 and 0.24 points respectively, when individuals between the 25th and the 75th percentile of the GVA/acre distribution are compared. The difference in GVA/acre in rupee terms between those at the 75th percentile of the transformed GVA/acre distribution and those at the 25th percentile, is of roughly 16,500 rupees (roughly 250 U.S. dollars or 833 PPP dollars[11]) per acre per year. Averaged output prices across space and time imply that the GVA/acre rupee difference translates into yields of 0.57 tons/acre (pigeon pea) and 1.25 tons/acre (wheat).

Table 3.7 presents results from the long term growth specification in Equation 3.2. Column (1) includes zero valued year-by-household GVA/acre observations, and these results imply that a 10 pp. increase in the growth rate of GVA/acre is associated a 0.04 pp. increase in the growth rate of BMI. Column (2) excludes zero-valued year-by-household GVA/acre observations. Around 90% of the excluded observations in column (2) are on account of households that dont farm in all four years or

[11]The PPP conversion factor used in based on the 2011 International Comparison Program (ICP) round accessed on the World Bank website at http://data.worldbank.org/indicator/PA.NUS.PPPC.RF on 4.4.2016.

in three out of four years. The effect of GVA/acre on BMI is stronger among these households, with a 10 pp. increase in GVA/acre growth rate being associated with a 0.15 pp. increase in BMI growth rate. The negative association between the growth rate of livestock income and the growth rate of BMI is possibly indicative of the well documented association between animal husbandry and human diarrhea and enteric infections (Zambrano et al. (2014)). The growth rate of none of the other sources of non-agricultural income is statistically associated with the growth rate of BMI.

In Table 3.8, we examine the effect of GVA/acre on women's BMI, broken down by the age-category of the woman. Across all three specifications, the impact of agricultural income on BMI is larger for younger women in the age-group 15-25 years, as compared to women in the older age group 25-49 years. The former effect is also estimated very precisely. Therefore, the impact of agricultural income is stronger for women who are, on average, significantly more likely to be underweight (recall the age-wise distributions presented in Figure 3.1(B)). A plausible explanation for the salient age-effect apparent in our results is that the diets of younger, more underweight women are more responsive to agriculture-income increases. This is especially true if people have a set point for their weight and stop eating when it is reached. For people at their set point, an increase in GVA should not lead to an increase in their BMI. Apart from diets, households may also respond to higher agricultural production by changing the intra-household allocation of labor force participation and diverting labor away from younger household members.

3.4.2 Empirical Insights on Agriculture-Nutrition Pathways

Next, we empirically test for the importance of home production for self-consumption, for nutrition. Under the non-separability of production and consumption decisions (Singh, Squire and Strauss (1986)), which arise in the presence of high market-transaction costs, we might find home production of food to have a significant effect on nutrition.

In Table 3.9, we formally test for whether production for own consumption is a possible pathway by which agricultural incomes might impact women's BMI. In an analogous regression, we examine the effects of food purchases, the results of which are presented in Table 3.10. We expect the two regressions to be symmetric, because own production and purchases together form well over 90% of the sourced by households (Figure 3.6)[12]. In both Table 3.9 and Table 3.10, we focus on the results in columns (2) and (3), as our preferred set of results. Here, we test for the effect of the source of food procurement, by accounting for the ratio of expenditure on a food group from a certain source as a ratio of total expenditure on that food group, controlling for overall expenditure shares of included food-groups, total food expenditure and the full set of time-variant controls from Table 3.5, col. 2. Col. 1 of both tables presents cross-sectional results with village fixed-effects for the sake of comparison and the specification in column (3) tests robustness to the exclusion of outlier values.

[12]Figure 3.5 shows overall expenditure shares for the different food groups among the sample households

We do not find production for own consumption to be an important pathway by which agricultural income affects nutrition. Only for cereals is the effect of own production marginally significant. On the other hand, we see in Table 3.10 that the purchase of pulses have a strong and statistically significant effect on women's BMI, though this effect is somewhat imprecisely measured when outliers are removed (col. 3). The market seems to be playing an important role in facilitating the consumption of protein rich and nutritious pulses. Nutritional improvements on account of market purchases of pulses among agricultural households, indicate an income effect. While we do see that very large changes in non-agricultural income sources (yearly jump from the first to the fourth quartile) do correlate with BMI improvements, the short-term and long-term specifications (Table 3.5 & Table 3.7) taken together, suggest a dominant association of agricultural income and BMI.

3.5 Concluding Remarks

Agricultural productivity growth has long been seen as a promising pathway towards reducing malnutrition, given it's high incidence among predominantly cultivator families in rural India. Our results encourage pursuing an agricultural growth strategy for addressing nutritional concerns, with a specific focus on womens malnutrition. Moreover, our results suggest exceptionally stronger effects for younger women, a demographic most at risk of being underweight, and among whom fertility is largely concentrated. Among pathways considered, we find own-production to be

only weakly associated with BMI increases but individual nutrition benefits from market purchases, especially of protein-rich pulses, to a larger extent. Given the relative strength of rural markets in India, as compared to countries in sub-Saharan Africa, we provide an important context to evaluate the income-nutrition pathway via market access to food. That increasing agricultural incomes also empowers women within households to allocate expenses towards more nutritious purchases is a hypothesis that requires more detailed consideration, but is consistent with the patterns in our data. While our results recommend a role for agricultural income increases to influence nutrition outcomes among the group of households that cultivate, they also show a trade-off between participation in own farm labor and nutritional gains. Therefore, investment in labor-saving agricultural technologies can have significant positive benefits in terms of improved personal health and nutrition.

Lastly, we also find a strong cross-sectional relationship between women's BMI and that of her children, as measured by weight-for-height z-scores of children under 5 (Table 3.11). Controlling for a set of village, household, mother and child level variables, mother's BMI is a very strong predictor of her child's weight-for-height z-score (p-value=0.005). This effect exists net of differences in household socio-economics, and suggests a more direct link between maternal health and empowerment with child weight. This effect is likely operational through multiple channels including, nutritionally, through breast-feeding, or more generally via mothers caring capacity. This result, in conjunction with recent literature examining the effect of womens empowerment on child nutrition (Coffey, Khera and Spears (2013)), (Imai et al.

(2014)), suggest, additionally, strong inter-generational nutritional benefits of agricultural productivity increases.

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Figures & Tables for Chapter 3

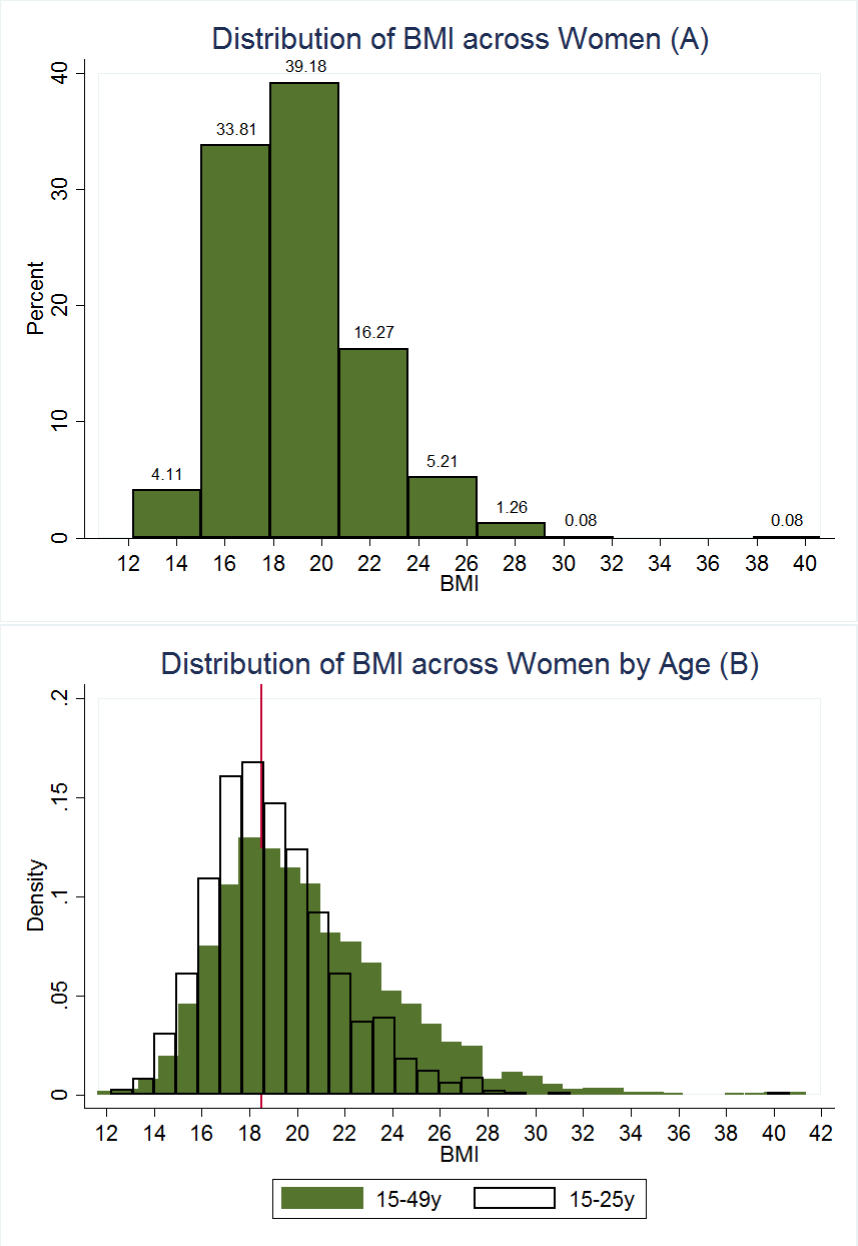

Figure 3.1: BMI Distribution of Sample Women (A), and BMI distribution by Age (B)

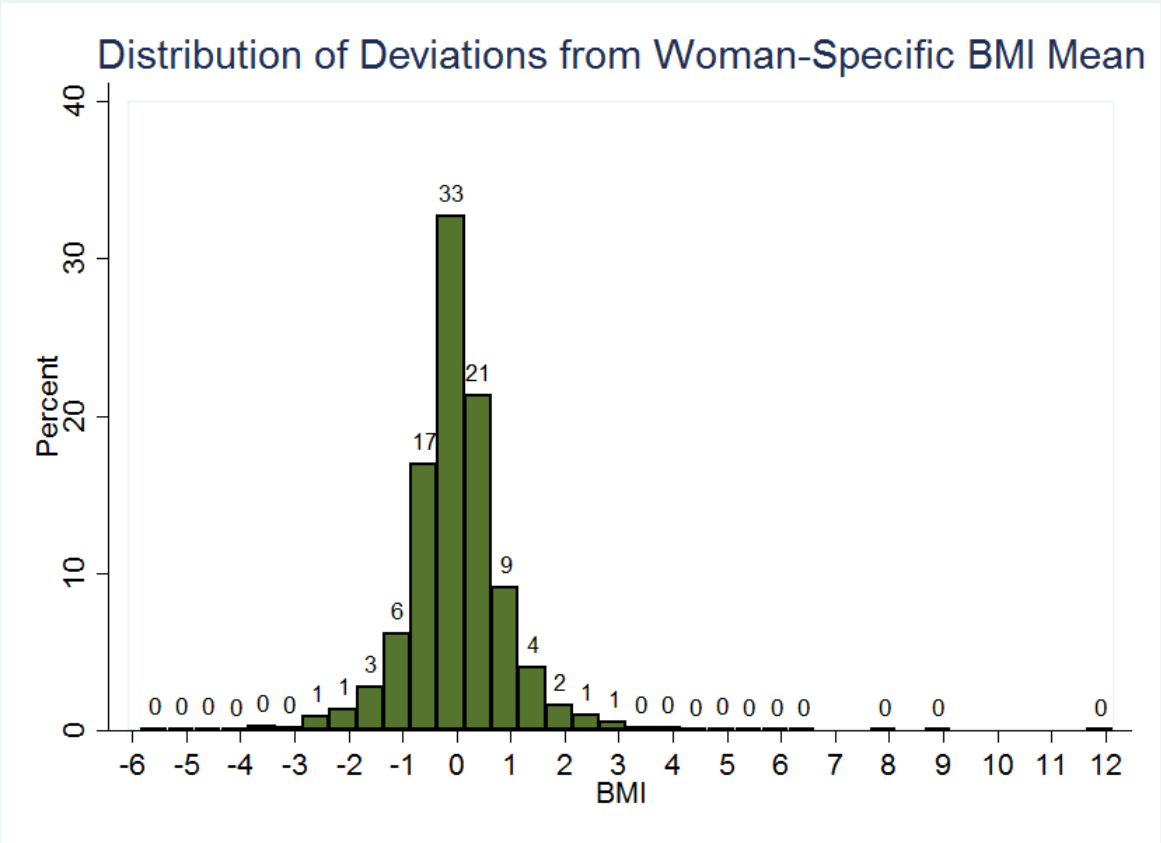

Figure 3.2: Distribution of Yearly Deviations from Woman-Specific BMI Means

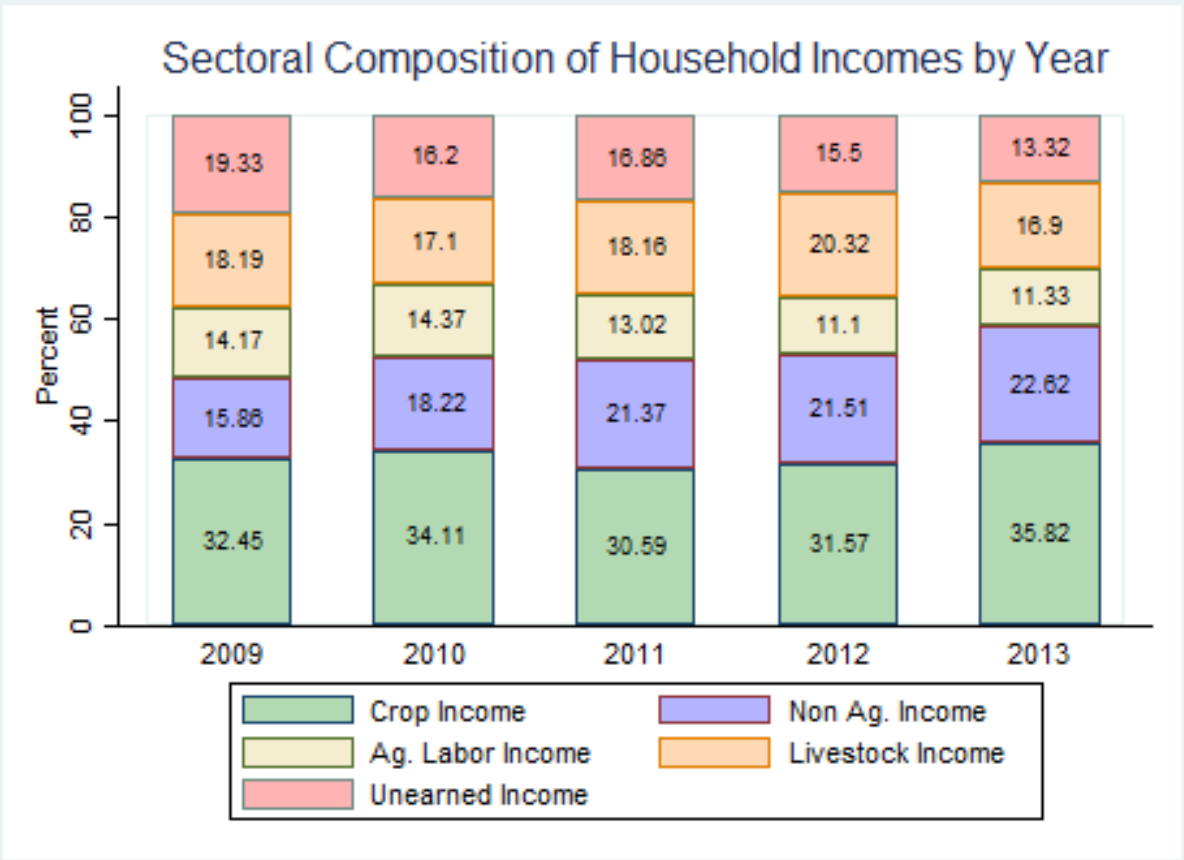

Figure 3.3: Sectoral Composition of Household Incomes from Different Sources, by Year

Figure 3.4: Proportion of Income Accruing to Women and Men from Non-Ag. Sector & Farming

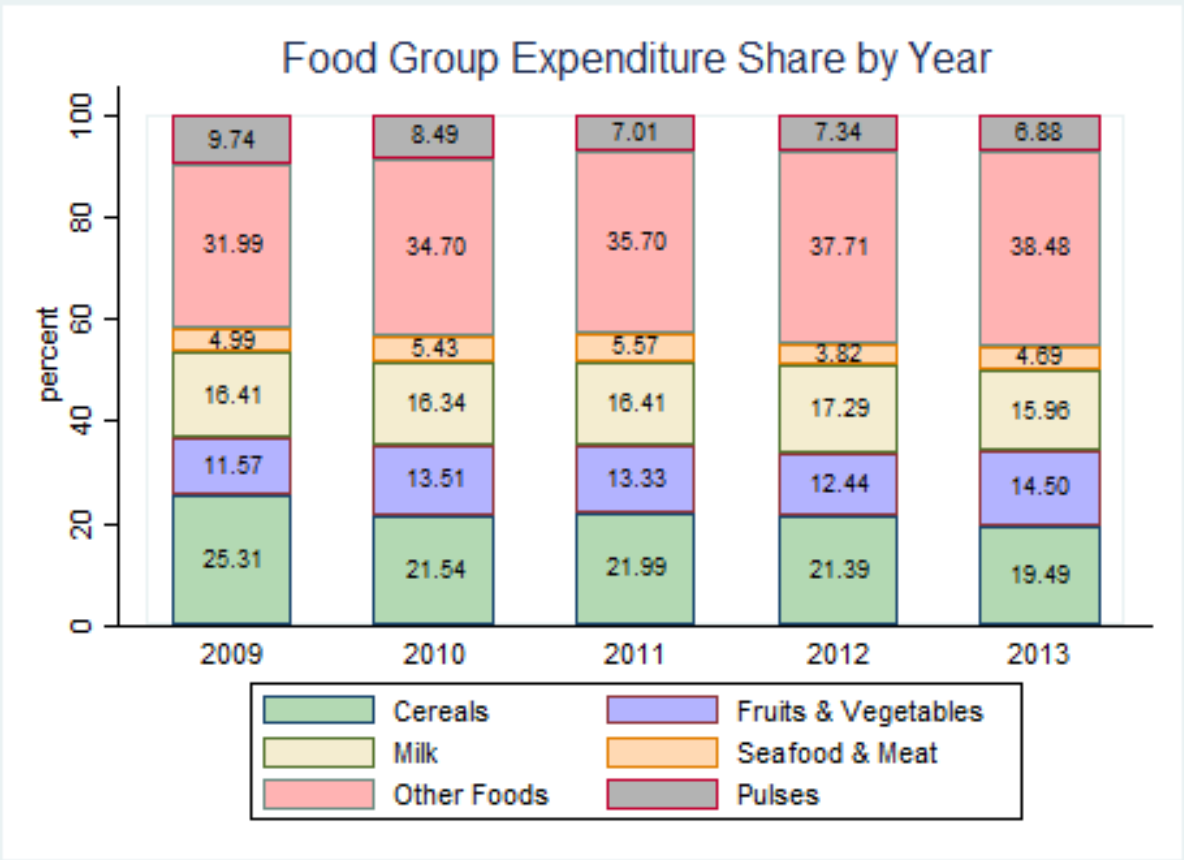

Figure 3.5: Household-Level Food Group Expenditure Share by Year

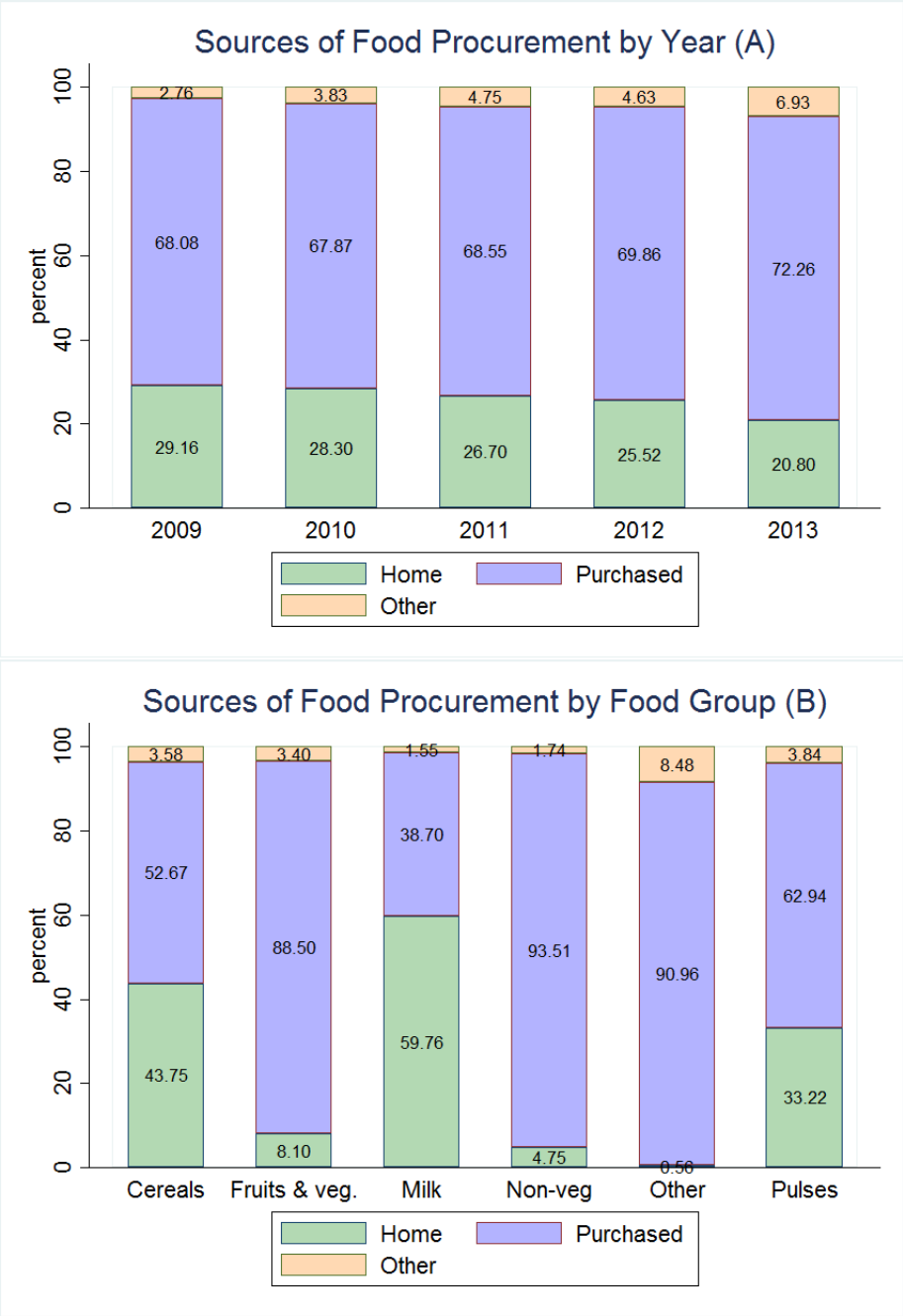

Figure 3.6: Sources of Food Procurement by Year (A), and Food Group (B)

Table 3.1: Descriptive Statistics of Main Variables used in Statistical Analysis

	2009		2010		2011		2012		2013	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
BMI	-	-	20.44	3.71	20.47	3.75	20.45	3.64	20.7	3.67
Age (in years)	29.9	9.87	30.54	10.03	30.5	9.85	30.46	9.91	30.71	10.06
Education (in years)	5.71	4.96	5.71	4.95	5.96	4.96	6.23	5.01	6.37	5
Household Size (no. of people)	6.12	2.84	5.95	2.8	5.96	2.8	6	2.83	6.12	2.92
GVA/acre ('000 rupees)	13.33	38.9	13.79	15.38	13.37	19.96	13.86	14.24	16.19	17.29
Cultivated Area (in acres)	5.6	8.91	5.82	9.02	6.42	11.17	6.14	10.65	6.45	11
% HHs in Farming	0.76	0.42	0.76	0.42	0.78	0.42	0.78	0.42	0.81	0.4
Farm Income ('000 rupees)	88.19	201.79	94.17	161.08	86.08	147.68	96.38	170.44	110.51	208.42
Livestock Income ('000 rupees)	31.54	42	34.26	43.77	39.25	53.93	46.1	61.51	39.22	57.18
Non-Ag. Income ('000 rupees)	24.2	57.58	30.7	65.18	37.43	71.4	39.78	71.74	38.9	67.89
Unearned Income ('000 rupees)	33.28	86.93	48.36	236.86	39.37	94.14	38.6	80.23	34.74	86.66
Ag. Labor Income ('000 rupees)	11.74	16.22	13.68	17.86	14.26	20.71	12.69	18.12	12.06	16.97
Total HH Income ('000 rupees)	189	263.23	221.52	343.33	216.8	227.36	233.91	237.41	235.64	274.45
Medical Expenditure ('000 rupees)	4.84	11.38	5.15	14.07	4.4	8.79	5.29	11.08	4.96	10.21
HH Food Expenditure ('000 rupees)	35.63	17.59	35.38	17.54	37.47	19.36	37.51	19.5	38.37	20.74
Cereal Share in Food Expenditure	0.25	0.08	0.22	0.06	0.22	0.07	0.22	0.08	0.2	0.08
% HHs with electricity	0.88	0.33	0.93	0.26	0.94	0.24	0.96	0.21	0.96	0.19
% HHs with water	0.52	0.5	0.51	0.5	0.53	0.5	0.53	0.5	0.56	0.5
% HHs with toilets	0.25	0.43	0.28	0.45	0.35	0.48	0.37	0.48	0.42	0.49
Village rainfall (cm/year)	78.76	17.27	100.3	21.82	74.58	26.16	61.11	25.18	90.81	29.49

Notes: (1) All income & expenditure variables are in real terms, expressed in 2009-10 rupees.
(2) "GVA/acre" refers to Gross Value Added/Acre

Table 3.2: Relationship between Agricultural Income & Women's BMI (Baseline Specification)

Independent Variable	Dependent Variable-BMI		
	(1)	(2)	(3)
GVA/acre	0.203*/+	0.112*	0.091**/*
(Cluster-Robust p-Value)	*(0.075)*	*(0.062)*	*(0.046)*
(Wild Bootstrap p-Value)	*(0.108)*	*(0.074)*	*(0.058)*
Cultivated Area	0.0387**	0.00303	0.00447
Ag. Sector Participation	-2.105*	-0.951*	-0.758*
Age	0.240***	-	-
Age Squared	-0.00204*	-	-
Constant	14.90***	20.03***	20.06***
Year FE	YES	YES	YES
Village FE	YES	YES	YES
Individual FE	NO	YES	YES
Extreme BMI Deviations Removed	NO	NO	YES
Observations	3,569	3,325	3,294

Notes: (1) Standard errors are clustered at the village level (2) Variable for "GVA/acre" has been transformed using an inverse hyperbolic sine transformation. "Cultivated Area" is in acres, Ag. Sector Participation is a dummy variable for whether or not a household farms. (3) Age and Age-Squared are important predictors of women's BMI and are included in all cross-sectional/village fixed-effects specifications. Age variables are omitted from the panel/individual fixed-effects specifications because of the inclusion of year fixed-effects. (4)*** p<0.01, ** p<0.05, * p<0.1, + p<0.15

Table 3.3: Changes in Effect-Size of GVA/acre due to Removal of Outliers

Independent Variable	Dependent Variable-BMI			
	None	5 smallest & 5 largest	10 smallest & 10 largest	15 smallest & 15 largest
GVA/acre	0.112*	0.0984*	0.0914*	0.091**/*
(Cluster-Robust p-Value)	*(0.062)*	*(0.063)*	*(0.064)*	*(0.046)*
(Wild Bootstrap p-Value)	*(0.074)*	*(0.086)*	*(0.080)*	*(0.058)*
Cultivated Area	0.00303	0.00675	0.0047	0.00447
Ag. Sector Participation	-0.951*	-0.804	-0.715	-0.758*
Constant	20.03***	20.01***	20.02***	20.06***
Year FE	YES	YES	YES	YES
Village FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Observations	3,325	3,314	3,305	3,294

Notes: (1) Standard errors are clustered at the village level
(2) *** p<0.01, ** p<0.05, * p<0.1., + p<0.15

Table 3.4: Relationship between Agricultural Productivity and Women's BMI (Pooled Cross-Section Results)

Independent Variable	Dependent Variable-BMI		
	(1)	(2)	(3)
GVA/acre	0.151	0.0996	0.0942
(Cluster-Robust p-Value)	*(0.191)*	*(0.374)*	*(0.406)*
Cultivated Area	0.0299*	0.0244*	0.0242*
Ag. Sector Participation	-1.624	-1.027	-0.97
Own Education	0.0785***	0.0522**	0.0525**
Family Size	-0.0087	-0.028	-0.0281
HH has Electricity	0.378	0.252	0.267
HH has Water	0.443	0.351	0.34
Livestock Income	-	-0.00387	-0.0031
Non- Ag. Income	-	0.0297	0.0306
Unearned Income	-	0.0609**	0.0600**
Ag. Labor Income	-	-0.0626***	-0.0614***
Medical Expenditure	-	0.0829**	0.0861**
Age	0.266***	0.255***	0.256***
Age Squared	-0.00215*	-0.00211*	-0.00211*
Constant	13.39***	13.20**	-0.00235**
Year FE	YES	YES	YES
Village FE	YES	YES	YES
Village Rainfall	NO	NO	0.00656*
Observations	3,568	3,565	3,565

Notes:(1) Standard errors are clustered at the village level (2)"GVA/acre", all income variables and the medical expenditure variable have been transformed using an inverse hyperbolic sine transformation. (3) *** p<0.01, ** p<0.05, * p<0.1, + p¡0.15

Table 3.5: Relationship between Agricultural Income and Women's BMI with Sequential Addition of Controls (Panel-Data Results)

Independent Variables	Dependent Variable-BMI			
	(1)	(2)	(3)	(4)
GVA/acre	0.117**	0.106*	0.0982**	0.0880**
(Cluster-Robust p-Value)	*(0.049)*	*(0.065)*	*(0.033)*	*(0.037)*
(Wild Bootstrap p-Value)	*(0.054)*	*(0.066)*	*(0.036)*	*(0.032)*
Cultivated Area	0.00536	0.00186	0.00694	0.00381
Ag. Sector Participation	-0.997*	-0.893	-0.820*	-0.725*
Family Size	-0.015	-0.0169	-0.0205	-0.0221
HH has Electricity	-0.177	-0.156	-0.210**	-0.190*
HH has Water	0.0662	0.0467	-0.00658	-0.0243
Livestock Income	-0.00605	-0.00594	-0.00239	-0.00232
Non- Ag. Income	0.000296	0.00212	0.00808	0.0098
Unearned Income	0.023	0.0218	0.0122	0.0112
Ag. Labor Income	0.00974	0.0121	0.00917	0.0114
Medical Expenditure	0.0149	0.0166	0.0145	0.016
Constant	19.91***	19.57***	20.05***	19.90***
Year FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Village Rainfall	NO	0.00428	NO	0.00392*
Extreme BMI Deviations Removed	NO	NO	YES	YES
Observations	3,325	3,325	3,294	3,294

Notes: (1) Standard errors are clustered at the village level
(2) "GVA/acre", all income variables and the medical expenditure variable have been transformed using an inverse hyperbolic sine transformation
(3) *** p<0.01, ** p<0.05, * p<0.1., + p<0.15

Table 3.6: Relationship between Agricultural Productivity and Women's BMI with Income Quartiles as Controls

Independent Variable	Dependent Variable-BMI			
	(1)	(2)	(3)	(4)
GVA/acre	0.116*	0.104*	0.0918**	0.0799**
(Cluster-Robust p-Value)	*(0.058)*	*(0.076)*	*(0.037)*	*(0.045)*
(Wild Bootstrap p-Value)	*(0.068)*	*(0.088)*	*(0.040)*	*(0.040)*
Cultivated Area	0.00423	0.00048	0.00682	0.00369
Ag. Sector Participation	-0.985*	-0.867	-0.759*	-0.649*
Family Size	-0.0205	-0.0234	-0.033	-0.0356
HH has Electricity	-0.153	-0.131	-0.196*	-0.174
HH has Water	0.0467	0.0266	-0.024	-0.0425
2nd Quartile Non-Ag. Income	-0.0336	-0.0218	-0.0599	-0.0494
3rd Quartile Non- Ag. Income	-0.084	-0.0637	0.0297	0.0484
4th Quartile Non- Ag. Income	0.086	0.116	0.223*	0.251*
2nd Quartile Livestock Income	-0.0675	-0.0569	-0.00393	0.00567
3rd Quartile Livestock Income	-0.0233	-0.0361	0.0346	0.0219
4th Quartile Livestock Income	-0.0859	-0.11	-0.0539	-0.0768
2nd Quartile Unearned Income	0.104	0.117	0.0177	0.0288
3rd Quartile Unearned Income	-0.00152	0.00384	-0.0408	-0.0359
4th Quartile Unearned Income	0.169*	0.187**	0.139	0.156*
2nd Quartile Ag. Labor Income	0.0495	0.0759	0.000158	0.0241
3rd Quartile Ag. Labor Income	0.13	0.15	0.111	0.13
4th Quartile Ag. Labor Income	0.0743	0.109	0.206*	0.239**
Medical Expenditure	0.0165	0.0176	0.0165	0.0174
Constant	20.04***	19.67***	20.157***	19.81***
Year FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Village Rainfall	NO	0.00467*	NO	0.00430**
Extreme BMI Deviations Removed	NO	NO	YES	YES
Observations	3,325	3,325	3,294	3,294

Notes:(1) Standard errors are clustered at the village level
(2) *** p<0.01, ** p<0.05, * p<0.1, + p<0.15

Table 3.7: Relationship between Agricultural Income Growth and BMI growth

Independent Variables	Dependent Variable-Growth Rate of BMI	
	(1)	(2)
	At least 2 years of GVA/acre ≥ 0	At least 2 years of GVA/acre > 0
Growth rate of GVA/acre	0.00362***	0.0153***
(Cluster-Robust p-Value)	*(0.007)*	*(0.001)*
(Wild Bootstrap p-Value)	*(0.006)*	*(0.000)*
Growth rate of Cult. Area	-0.000347	0.000103
Growth rate of Family Size	0.00311	0.0161
Growth rate of Water Access	-0.0147	-0.0062
Growth rate of Elec. Access	0.00392	0.0119
Growth rate of Non. Ag Income	-0.000793	-0.0004
Growth rate of Unearned Income	0.00033	0.000508
Growth rate of Livestock Income	-0.00293***	-0.00330**
Growth rate of Ag. Labor Income	0.000224	-0.000273
Growth rate of Medical Expenditure	-0.00138	-0.00166
Growth rate of Rainfall	0.0246	0.0205
Constant	0.0175***	0.0156***
Observations	1045	827

Notes: (1) Standard errors are clustered at the village level
(2) *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Relationship between Agricultural Income and Women's BMI- by Age

Independent Variable	Dependent Variable-BMI		
	(1)	(2)	(3)
Younger#GVA/Acre	0.150**	0.137**	0.119***/**
(Cluster-Robust p-Value)	*(0.016)*	*(0.019)*	*(0.009)*
(Wild Bootstrap p-Value)	*(0.026)*	*(0.026)*	*(0.018)*
Older#GVA/Acre	0.109*	0.0978+	0.0787*
(Cluster-Robust p-Value)	*(0.079)*	*(0.11)*	*(0.078)*
(Wild Bootstrap p-Value)	*(0.088)*	*(0.106)*	*(0.088)*
Age Group	0.163	0.183	0.0539
Cultivated Area	0.00565	0.00219	0.00423
Ag. Sector Participation	-0.986*	-0.881	-0.705*
Family Size	-0.005	-0.00692	-0.0144
HH has Electricity	-0.182	-0.161	-0.194*
HH has Water	0.0723	0.0529	-0.0184
Livestock Income	-0.00589	-0.00579	-0.0022
Non- Ag. Income	-0.00015	0.00166	0.00941
Unearned Income	0.0226	0.0214	0.0108
Ag. Labor Income	0.00992	0.0123	0.0115
Medical Expenditure	0.0144	0.0161	0.0155
Constant	19.74***	19.39***	19.62***
Year FE	YES	YES	YES
Individual FE	YES	YES	YES
Village Rainfall	NO	0.00425	0.00389*
Extreme BMI Deviations Removed	NO	NO	YES
Observations	3,325	3,325	3,294

Notes:(1) Standard errors are clustered at the village level
(2) Age Group=0 if 25< age $\leq$ 49 and Age Group=1 if 15$\leq$ age $\leq$25
(3) *** p<0.01, ** p<0.05, * p<0.1, + p< 0.15

Table 3.9: Own Production of Different Food Groups and Women's BMI

Independent Variables	Dependent Variable-BMI		
	(1)	(2)	(3)
Own prod. ratio-cereals	-0.0789	0.181+	0.173+
(Cluster-Robust p-Value)	*(0.800)*	*(0.117)*	*(0.108)*
(Wild Bootstrap p-Value)	*(0.795)*	*(0.164)*	*(0.148)*
Own prod. ratio-fruits & veg.	0.997	0.272	0.451
(Cluster-Robust p-Value)	*(0.296)*	*(0.686)*	*(0.401)*
(Wild Bootstrap p-Value)	*(0.342)*	*(0.848)*	*(0.611)*
Own prod. ratio-milk	-0.429	0.0824	-0.0249
(Cluster-Robust p-Value)	*(0.229)*	*(0.680)*	*(0.859)*
(Wild Bootstrap p-Value)	*-0.226*	*(0.696)*	*(0.861)*
Own prod. ratio-other foods	10.46***	-0.0376	0.112
(Cluster-Robust p-Value)	*(0.000)*	*(0.996)*	*(0.883)*
(Wild Bootstrap p-Value)	*-0.004*	*(0.920)*	*(0.925)*
Own prod. ratio-pulses	-0.452	-0.332+	-0.218
(Cluster-Robust p-Value)	*(0.227)*	*(0.106)*	*(0.212)*
(Wild Bootstrap p-Value)	*(0.254)*	*(0.134)*	*(0.238)*
Overall expenditure share- cereals	-1.254	1.569	0.558
Overall expenditure share- fruits & veg.	0.0479	-0.225	-0.982
Overall expenditure share- milk	2.933	2.683	1.138
Overall expenditure share- other foods	-1.36	0.302	-1.045
Overall expenditure share- pulses	-0.534	1.629	1.373
Total food expenditure	0.914**	-0.176	-0.1
Age	0.248***	-	-
Age Squared	-0.00213*	-	-
Constant	5.227	20.41***	20.51***
Year FE	YES	YES	YES
Village FE	YES	YES	YES
Individual FE	NO	YES	YES
Extreme BMI Deviations Removed	NO	NO	YES
Time Variant Controls (from Table 3.5, col. 2)	NO	YES	YES
Observations	3,566	3,325	3,294

Notes:(1) Own production ratio for a food-group is the ratio of the imputed value (using market prices) of home production as a fraction of total expenditure on the item. (2) Standard errors are clustered at the village level (3)Variable for "total food expenditure" has been transformed using an inverse hyperbolic sine transformation. (4)*** p<0.01, ** p<0.05, * p<0.1, + p<0.15

Table 3.10: Food Purchases of Different Food Groups and Women's BMI

Independent Variable	Dependent Variable-BMI		
	(1)	(2)	(3)
Purchase ratio-cereals	0.089	-0.194^{+}	-0.192*
(Cluster-Robust p-Value)	*(0.792)*	*(0.114)*	*(0.085)*
(Wild Bootstrap p-Value)	*(0.770)*	*(0.138)*	*(0.11)*
Purchase ratio-fruits & veg.	-0.49	-0.378	-0.453
(Cluster-Robust p-Value)	*(0.540)*	*(0.490)*	*(0.321)*
(Wild Bootstrap p-Value)	*(0.557)*	*(0.693)*	*(0.511)*
Purchase ratio-milk	0.258	-0.0349	0.0141
(Cluster-Robust p-Value)	*(0.400)*	*(0.796)*	*(0.899)*
(Wild Bootstrap p-Value)	*(0.388)*	*(0.837)*	*(0.869)*
Purchase ratio-other foods	1.794*/**	0.42	0.484
(Cluster-Robust p-Value)	*(0.057)*	*(0.235)*	*(0.168)*
(Wild Bootstrap p-Value)	*(0.040)*	*(0.184)*	*(0.132)*
Purchase ratio-pulses	0.474	0.473*	0.322*/$^{+}$
(Cluster-Robust p-Value)	*(0.218)*	*(0.057)*	*(0.095)*
(Wild Bootstrap p-Value)	*(0.222)*	*(0.076)*	*(0.128)*
Overall expenditure share- cereals	-0.999	1.494	0.469
Overall expenditure share- fruits & veg.	-1.041	-0.385	-1.068
Overall expenditure share- milk	2.316	2.614	1.058
Overall expenditure share- other foods	0.331	1.659	1.405
Overall expenditure share- pulses	-1.728	0.323	-0.956
Total food expenditure	0.978**	-0.144	-0.0656
Age	0.252***	-	-
Age Squared	-0.00220*	-	-
Constant	2.416	19.89***	20.01***
Year FE	YES	YES	YES
Village FE	YES	YES	YES
Individual FE	NO	YES	YES
Extreme BMI Deviations Removed	NO	NO	YES
Time Variant Controls (from Table 3.5, col. 2)	NO	YES	YES
Observations	3,566	3,325	3,294

Notes: (1) Purchase ratio for a food-group is the ratio of the value of food purchase as a fraction of total expenditure on the item.
(2) Standard errors are clustered at the village level
(3) Variable for "total food expenditure" has been transformed using an inverse hyperbolic sine transformation. (4)*** p<0.01, ** p<0.05, * p<0.1, + p<0.15

Table 3.11: Relationship between Child's Weight-for-Height & Mother's BMI

Independent Variable	Dependent Variable- WHZ	
Mother's BMI	0.0628***	0.0660***
(Cluster-Robust p-Value)	*(0.005)*	*(0.003)*
(Wild Bootstrap p-Value)	*(0.010)*	*(0.006)*
Age in Months	-0.00658	-0.00664
Sex	-0.123	-0.129
Birth Order	-0.00634	-0.00299
Mother's Education	0.0115	0.011
Mother's Age	-0.0148	-0.0176
GVA/acre	-0.0962	-0.104
Cultivated Area	-0.00605	-0.00497
Ag. Sector Participation	1.348	1.423
Livestock Income	0.00824	0.00756
Non- Ag. Income	0.0203	0.0193
Unearned Income	0.0451***	0.0449***
Ag. Labor Income	-0.00537	-0.00726
Medical Expenditure	0.0528	0.0449
HH has Water	0.117	0.0952
HH has Toilet	0.0722	0.0544
Constant	-2.417**	-1.652*
Year FE	YES	YES
Village FE	YES	YES
Village Rainfall	NO	-0.00822
Observations	709	709

Notes: (1) Standard errors are clustered at the village level (2) "GVA/acre" and all income variables have been transformed using an inverse hyperbolic sine transformation. (3) *** p<0.01, ** p<0.05, * p<0.1, + p<0.15