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RIVERSIDE

Essays on Health and Public Policy

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Aparajita Dasgupta

August 2013

Dissertation Committee:

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ABSTRACT OF THE DISSERTATION

Essays on Health and Public Policy

by

Aparajita Dasgupta

Doctor of Philosophy, Graduate Program in Economics

University of California, Riverside, August 2013

Professor Anil B. Deolalikar, Co-Chairperson

Professor Mindy Marks, Co-Chairperson

This dissertation is composed of two essays focusing on some key emerging issues of health economics in developing countries. In the first chapter, I examine the role of the largest public works program in the world- the National Rural Employment Guarantee Scheme (NREGS) - in buffering the negative effects of early childhood exposure to rainfall shocks on long-term health outcomes. Collecting very detailed administrative records of rainfall shocks and policy coverage, I integrate it with a rich household level panel data from the Young Lives Survey, that follows children from year 2002 to 2010. Using three waves of the panel data spanning over eight years, the study employs individual-fixed effects estimation to analyze the extent of catch-up in height for age for the rural sample exploiting the phase wise variation in roll out of the policy across households. We find while the program does not help correct long term past health deficiencies, it is useful in buffering recent drought shocks. Interestingly, we find the extent of this mitigation varies by policy relevant subgroups, where we find it benefits significantly the poor households from lower caste and lower educational background. We find early drought exposure decreases the height for age score by 0.4 standard deviations and increases average stunting rate by 8%. For individuals exposed to drought, we find an increase in one standard deviation in average program days increases height-for-age by around 0.26 standard

deviations, which is about half the rural-urban gap in terms of magnitude. The findings indicate while there is long-run impact of early-life conditions on health several years later, access to the program helps to partially mitigate recent shocks but not correct for longer-term past deficiencies. Since there is little scope of remediation in correcting past deficiencies, the study highlights the key role that a social protection policy can play in safe-guarding households against such negative shocks.

The second chapter examines the extent of reporting biases in self-reported health response across demographic sub-groups using the unique nationally representative data collected by the World Health Survey-SAGE survey from India, that has self-reported assessments of health linked to anchoring vignettes as well as objective measures like body mass index and performance tests on a range of different domains of health. Analysis of the vignettes responses reveals a systematic under-reporting of worse health among the individuals from less developed states in India, which is statistically significant across various health domains. While males and urban residents were found to systematically under-report ill-health, individuals over 60 years were found to over-report ill health. Utilizing a battery of objective health measures, we introduce a methodology to implicitly test the assumption of ‘response consistency’ in vignettes and confirm its validity by identifying similar systematic bias in self-reported health responses across covariates. Further examination of reporting bias by exploiting the individual fixed effects reveals that substantial variation in self-reported health remains unexplained even after controlling for the usual covariates. The results seem to suggest that systematic differences in self-reported health response, even within a country, needs to be accounted for while making inter group comparisons valid and lends support to the use of the vignette technique for identifying this bias.

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Chapter 1

Can the Major Public Works Policy Buffer Negative Shocks in Early Childhood?

Evidence from Andhra Pradesh, India

Aparajita Dasgupta¹

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Abstract

The study examines the role of the largest public works program in the world-the National Rural Employment Guarantee Scheme (NREGS) - in buffering the negative effects of early childhood exposure to rainfall shocks on long-term health outcomes. Exploiting the spatial and temporal variation in NREGS coverage, the study estimates the extent to which nutritional shocks in early childhood can be offset by access to the policy. The study employs a unique identification strategy by integrating detailed administrative records of drought shock and phase-wise roll-out of NREGS with a household level panel data-the Young Lives survey- conducted over three waves (2002, 2007 and 2009-10) in the state of Andhra Pradesh, India. Using individual fixed effects estimation the study finds that while the policy does not help correct for long term past health deficiencies it is useful in buffering recent drought shocks, which varies by policy relevant sub-groups.

JEL Classification: I18, J13, O22

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1.1. Introduction

Exposure to negative shocks in early childhood is known to significantly affect the health and educational outcomes of population, even more so in developing countries. Increased climatic variability over time poses special challenges for child nutrition especially among subsistence farmers depending on rain-fed agriculture. Additionally, there has been no operational practice to forecast drought (Gore et al., 2010) where such an event may often lead to adverse outcomes such as loss of land rights against debt and declining nutrition levels for the poor majority of population. With a large proportion of households depending on agriculture -a highly volatile source of subsistence- the effects may be worse for the rural poor who often lack access to formal credit markets to smooth consumption.

In such a setup, rainfall shocks can lead to substantial reduction in household income, which can significantly reduce investments in children often compromising their calorie intake. The poor households often resort to sub-optimal coping mechanisms like taking children out of school or defer healthcare in response to such temporary shocks (Subbarao et al. 2012). This is a serious concern as the investments in early childhood can have significant impacts on human capital attainment and achievements as adults (Hoddinott and Kinsey (2001); Maccini and Yang (2009)). While the long term consequences of malnutrition during childhood are well established in the literature, little is known about the extent to which individuals are able to mitigate the deficits in health outcomes through the availability of social protection schemes.

Although stunting might be permanent when nutritional deficits begin early, nutritional remediation can still take place as long as the critical period for growth remains open. Therefore, it is important to study the vulnerability that a child faces when exposed to shocks that risk child nutrition and health by a decline in household income/food availability. Further it is very important to identify the extent to which individuals are able to compensate and offset these

negative effects when a social safety net is in place and examine additionally whether the mitigation varies by policy-relevant demographic subgroups.

Employment generating programs are expected to support vulnerable households assuring nutrition security during economic downturns. A recent comprehensive World Bank review (2012) of public works program across countries highlights the dearth of systematic evidence on effectiveness of public works programs in serving as safety nets despite their rapid adoption in diverse country settings. In the context of the major public-works policy in India, few studies have focused on its labor market impacts and self-targeting mechanism as opposed to examining its role in social protection. In this study we systematically examine the causal impact of the National Rural Employment Guarantee Scheme (NREGS) in mitigating effects of negative rainfall shocks on children's long-term health outcome taking evidence from rural Andhra Pradesh, India.

This study integrates a rich panel data from the Young Lives Survey following children across a span of eight years- with detailed administrative records of rainfall shocks and roll out information of program access. The identification strategy is to compare the trajectory of the height for age scores of children with and without program access interacted with drought shocks between year 2002 and 2010. Since the policy is first targeted to the poorer districts and also involves voluntary participation from households, the potential selection bias in estimates is addressed by including individual fixed effects which account for time invariant unobservable individual heterogeneities. Additionally we were also able to control for a host of time varying features that might have an independent effect on the outcome of interest. The estimates indicate that while drought significantly reduced height-for-age by 0.4 standard deviations, access to the program was able to mitigate the negative impact of drought shocks from last year, as reflected by an increase of 0.26 standard deviations in height-for-age. However it was not found to be able

to correct for longer-term past deficiencies (as captured by exposure to cumulative drought shocks from the birth year).

This paper contributes to the existing literature on a number of aspects. First, utilizing a rich set of detailed data on weather shocks and policy coverage and integrating with new panel data, the study is one of the first few ones to examine the causal impacts of a social protection policy to correct for past deficiencies relevant to child health in the long-run. While there exists a body of literature on the effects of early childhood shocks on human capital outcomes, the issue of how the effect can be mitigated under a public intervention is relatively understudied. Also one requires sufficiently integrated data sets in order to examine this question. Here we were able to use anthropometric measures of the child at different ages and control for inherent healthiness as opposed to using self-reported health outcomes. Furthermore, unlike past studies, I collected² and used very detailed information at the mandal (sub-district level) for rainfall shocks, program availability, and community level measures of health-infrastructure. This enabled me to control for a host of factors that influence child health independently, substantially accounting for the selection problem arising from inherent unobservable differences by families who decide to participate in the program. Second, while the existing literature for developing countries mostly focused on a rather extreme health outcome - child mortality, we were able to focus on malnutrition/child-stunting among survivors. Third, this paper is the first to examine its causal impact in remediating negative impacts of shocks on catch-up growth in children. Finally, we were able to comment on the differential impact of the mitigation across the demographic features of the child by age, gender, caste and caregiver's education, which brings out the vulnerability of the households by demographic subgroups, again crucial for policy insights.

² I collected and compiled the mandal-level information of rainfall and health facility over time from various years of Handbook of Statistics for each sample district in Andhra Pradesh by visiting the Directorate of Economics and Statistics, Government of Andhra Pradesh in Hyderabad.

The next section discusses the background and implementation of the NREGS in India. This is followed by an outline of the conceptual framework in section 1.3 highlighting how long-term health evolves under shocks and its potential mitigation under social protection policy. In section 1.4 the empirical specification is laid out. The datasets and the relevant descriptive statistics are discussed in section 1.5. Section 1.6 presents the main empirical results followed by a brief discussion of the policy insights and future work.

1.2 The Program: National Rural Employment Guarantee Scheme (NREGS)³

The National Rural Employment Guarantee Scheme (NREGS), which is now the largest public works program in the world (Azam et al. 2012), came into force in February 2006 under the legislative framework of the National Rural Employment Guarantee Act (2005). By 2010, the National Rural Employment Guarantee Act (NREGA) reached 52 million households across the country. The scheme provided a legal guarantee for 100 days of employment in every financial year to adult members of any rural household willing to do unskilled manual work at the statutory minimum wage of Rs.120⁴ (US\$2.64) per day in 2009 prices. Employment is required to be given within fifteen days of application for work, if it is not then daily unemployment allowance has to be paid (GOI, 2008). Wages are required to be disbursed generally on a weekly basis but it cannot be beyond a fortnight⁵ after the work has taken place. During the financial year 2010–11 Andhra Pradesh provided 274.8 million person days of employment (Galab et al. 2011). The idea is to encourage self-selected participation from those individuals who need it most or those hit by

³ NREGA is now known as MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Act)

⁴ In comparison, farm wage typically hovers around of 100-150 rupees depending on agricultural season.

⁵ Although according to the [PACS-CSO survey\(2007\)](#) , the majority of workers received their wages within 30 days for the aggregate sample of Indian state.

an idiosyncratic shock. Several features of the program relevant for the empirical strategy in the study are discussed in the following section.

1.2.1 Public-works as a safety net

NREGS was introduced in India with an aim of improving the purchasing power of the rural people, primarily providing semi-skilled or unskilled work to people living in rural India, whether or not they were below the poverty line. The purpose of this scheme was to create strong social safety net for the vulnerable groups, increase female labor-force participation, create durable and productive assets⁶ in rural areas that encourage sustainable development and reduce rural-urban migration. The evaluation report from Ministry of Rural Development (2011) finds the policy resulted in reduction in the distress-migration of labor and a rise in expenditure on food and non-food items, which again can have a strong association with child growth.

Berg et al. (2012) found the program access boosted the real daily agricultural wage rates by 3.13 per cent with a lag of 6 to 11 months. Uppal (2009) reports positively about the self-targeting mechanism under the NREGS and notes that poorer and schedule caste households were more likely to register for this work which had significantly reduced the likelihood of children in the household being required to work. Dutta et al.(2012) mentions that although NREGS was able to reach the rural poor, backward castes, and bring women into the workforce, its targeting performance varied by state. There is evidence that poorer states were unable to meet with the demand for job under this program thereby limiting availability of the scheme where it could benefit the most. However for the current sample state of Andhra Pradesh recent evidence (Subbarao et al.2012) indicates it as one of the forerunners in digitizing all the records of

⁶ [World Bank report \(2011\)](#) mentions the policy has only been successful in generating employment but not so in terms of asset creation.

transactions across multiples sites and levels of the program and is the only state in India to have institutionalized social audits to promote effective program monitoring.

1.2.2 Gender-sensitive component of NREGS

The scheme promotes women's participation in the labor force through a one-third quota for women in each state and also guarantees equal wages to both men and women workers.

According to the official records for NREGS, the share of women workers was found to be greater in Andhra Pradesh than nationally in 2011 (National average share for women being 50.1 %, while in Andhra Pradesh it is 57.5 %). In order to encourage participation of mothers with very young children, the program made the presence of child care facilities mandatory⁷ at all sites where more than five children under the age of six were present. However in the third round of the survey when the program has been already universalized, about 24% of the sample who did not participate in the scheme mentioned absence of child care centre as the reason. Recent evidence indicates the lack of child care centre in work-site as one of the significant deterrents for non-participation of women.

Since the prospects are typically worse for women in private casual wage work in India the provision of equal wages should have positive impacts on female participation. As argued by Imbert et al. (2011) NREGS has a sharper impact on female labor force participation⁸ than that of males. Azam et al. (2011) found wages for female casual laborers increased by 8 percent in participating districts as compared to nonparticipating districts. Zimmerman (2012) finds NREGS led to a substantial increase in the private-sector casual wage for women, the effects being

⁷ In spite of this provision the program has only 8.74% of registered respondents reported the availability of on-site child-care center in the second round (Galab, 2008).

⁸ Khera et al. (2009) points that NREGA wages implied a substantial jump in the earning potential for women at the national level.

concentrated in the main agricultural season. Hence if we believe that average women's participation in labor market has increased because of the program it has important associations for child well being⁹, the outcome of our interest.

1.2.3 Implementation of NREGS

The Government has implemented the scheme in phase-wise manner making use of a 'backwardness index' -comprising agricultural productivity per worker, agricultural wage rate, and Scheduled Caste/Scheduled Tribe population, developed by the Planning Commission. The first phase of the scheme was rolled out in 200 districts of the country from February 2006. In phase two, additional 130 districts were included from April 2007 (total 330 districts). From April 2008, in phase three, it was universalized and extended to all 596 rural districts in the country. For Andhra Pradesh the program roll out expansion across all its districts is shown in Figure 1.1- first phase included 13 districts in 2005, then to further six districts in 2007 and three more districts in 2008, to cover all 22 districts in the state.

Importantly for our identification strategy, four of the Young Lives sample districts (comprising of 11 mandal sites) were covered by the NREGS in the first phase of implementation in 2005-06 (Anantapur, Mahaboobnagar, Cuddapah, Karimnagar), with the addition of one more sample district Srikakulam (comprising of 4 mandal sites) - in 2007, coinciding with second phase of implementation, and lastly the district of West Godavari(with two mandal sites)was included in 2008- coinciding with phase three of the program expansion. Two out of six rural districts covered by Young Lives fell within the second and third phases, and in these two districts a large proportion of the Scheduled Tribe households were covered.

⁹ Women's independent income benefit household nutrition and child health, both through increase in household income as well as through an increase in women's status, autonomy and decision-making power specially those relating to nutrition, immunization and feeding practices (Smith, 2001).

The current study utilizes this variation in timing of the treatment using the phase wise expansion across the mandals, where the phase one locations (66% of the current sample) were the ones to get the program by the second round of the survey in 2007, illustrated in details in the empirical strategy section.

1.3 Conceptual Framework: Shocks, Child Vulnerability and Remediation

In order to discuss the potential impacts of the employment guarantee scheme on child outcomes in a simple analytical framework, the underlying hypothesis examined in this study is that direct positive income from wages earned from public work can feed into child investments in an otherwise situation of crises protecting the long-term health status. Stunting¹⁰, or low height-for-age, is a measure of chronic malnutrition and is generally considered a long-term indicator for health status. Earlier studies have pointed that stunting might be permanent when nutritional deficits begin early and are prolonged. Hoddinott and Kinsey (2001) find that droughts in rural Zimbabwe occurring between the ages of 0 and 12 months lead to significant reductions in child height when measured 12 months later. Maccini and Yang (2009) find a strong relationship between rainfall in the birth year and adults' health and socio-economic outcomes for women but not for men in Indonesia. Almond et al.(2011) points that even relatively mild prenatal exposures can result in lower birth weights, which can have persistent effects.

Despite the prevailing view that height deficits are hard to correct for after the first two years of a child's life, catch-up growth has in fact been documented in several studies from developing countries until the age of 12 years(Cameron et al. 2005). There is evidence that

¹⁰ The rate of stunting is severely high in developing countries including India -having the highest number of stunted children below the age of 5 in the world (Unicef 2009). In Andhra Pradesh, according to National Family Health Survey (NFHS-3, 2006) prevalence of malnutrition among children (0-59 months) is very high (32.5% underweight 42.7 % stunted and 12.2% wasted).

undernourished children from poor families who were adopted, by age five, into middle-class families reflected accelerated growth rates in adolescence (Allen et al. 2001). These results suggest that there is a large potential for catch-up growth in children into the preadolescent years. Additionally the medical literature in this regard points that there exists biological potential for catch-up in response to clinical interventions, which is explored in some studies focusing on catch-up growth (Deolalikar, 1996; Fedorov and Sahn, 2005; Alderman et al, 2006; Mani, 2008).

Martorell et al. (1994) survey evidence from medical literature and find evidence of catch up growth when living conditions were improved, especially for younger children. Outes et al.(2012) point that nutritional remediation can take place and catch up growth can be achieved as long as the critical period for growth remains open. Few studies in this regard point the potential for early nutritional intervention in accelerating growth. Schroeder et al. (1995) find that nutritional supplementation has a significant impact on growth for kids under 3 year olds in Guatemala. Yamano et al. (2005) emphasize in the context of rural Ethiopia, that food aid can compensate the negative effects of early shocks, but that inflexible targeting, endemic poverty and low maternal education often keep stunting at high levels despite such interventions. In Mexico, de Janvry et al., (2006) found that conditional cash transfer protects education, particularly that of girls, and thus fosters the formation of human capital, offsetting shocks such as parental unemployment or illness. For the case of public works component of Ethiopia's Productive Safety Net Programme (PSNP) Gilligan et al. (2009) found modest but positive effects on food security (improved by 0.40 months), and livestock holdings.

In terms of the evidence base of social protection policies, a recent systematic review of Hagen-Zanker, et al. (2011) points out that there were significantly more studies available on cash transfers compared to employment guarantee programs, indicating further need for systematic evidence on the impacts of the latter. In particular the recent review discussing the impacts of

social safety net Dercon (2011) indicated there is no evidence till date on the effectiveness of NREGS in safeguarding nutritional outcomes in rural poor households. In this context, it is immensely important to see to what extent the recent large scale public-works intervention in India- in the form of provision of an employment guarantee scheme for rural households- enables individuals to buffer negative shocks and correct nutritional deficiencies in early childhood.

1.4 Empirical Specification and Identification

The study examines whether access to the program is able to protect the households during shocks from the irreversible long-term damage induced by the different sub-optimal coping mechanisms that worsen long term child outcomes. Utilizing the temporal and spatial variation on program roll out time we compare the child nutritional outcomes across mandals with and without the program interacted with the exogenous drought variable.

The main outcome variable in our analysis is height-for-age z-score¹¹ which is a standardized measure of health status and is a well established long run indicator of individual health status especially among children (Martorell, 1999). It shows the height of the child relative to an international reference group of healthy children. Since height is a stock variable that reflects all past inputs into child health including the impact from past shocks and effect of the child level unobservables, it gives a cumulative picture of the child's overall growth status. We also use average stunting percent in mandal as another outcome variable to get an aggregate picture of program impact on the health outcome at the community level.

¹¹ This analysis uses height-for-age z-score as an indicator of catch-up growth following the rationale pointed by Cameron et al.(2005). First, they note the correlation between baseline and follow-up height is dependent on the ratio of height standard deviations of the two measurements, which in contrast, z-scores are not subject to, as they already take into consideration reference groups of equal age and sex. The second justification is that demonstration of catch-up growth needs to be compared with growth in a control group, which z-score measurement fulfills but a single height measurement does not. Third, the authors note that by using z-score measurements, catch-up growth may be separated from correlations predicted by regression to the mean.

In estimating the effect of the employment guarantee scheme there can be a potential serious problem of selection that arises at two levels, first from the targeted roll-out of the program and second from the self-selection mechanism¹² by which the scheme operates giving rise to potential econometric issues. The issue of self-selection cannot be simply done away by using administrative records of roll-out as the phases were also determined according to the backwardness index of the district. Hence, within a particular mandal if poorer households -with worse-off outcomes to begin with- self-select themselves into the scheme, then simple OLS regression estimates would likely be downward biased. In contrast if the more informed and well-connected households (among the poor households) take advantage of the scheme first, then estimates without fixed effects might be biased upwards in measuring the impacts of the scheme. By using individual-fixed effects estimation we could reasonably reduce these individual-specific but time invariant unobservable heterogeneities.

Additionally, the fixed effects approach helps explore the dynamics related to the persistence of shocks across individuals controlling unobserved heterogeneity between families that influences height. Thus we model the determinants of long-term child health (as reflected by height-for-age z-scores) status as follows:

$$(1) \quad H_{ijt} = \beta_1 \text{Drought}_{ijt-1} + \beta_2 \text{Coverage}_{ijt} + \beta_3 (\text{Drought}_{ijt-1} * \text{Coverage}_{ijt}) + \sum \beta_j X_{ijt} + \alpha_i + \varepsilon_{ijt}$$

where t=survey year (2002;2007,2009-10)

H_{ijt} is the height-for-age z-score of the i^{th} child from the j^{th} mandal measured in survey year t . α_i represents the individual fixed effects. $\text{Drought}_{ijt-1}^{13}$ represents a measure of negative

¹² Uppal (2009) finds that households hit by drought were 10.7% more likely to register for the NREGS than other households.

¹³ The drought variable is defined in reference to the last monsoon season, which predates the timing of the program information; in other words, program is not contemporaneously defined with drought. The households in the second round were all interviewed in 2007 (Jan- May) and were merged with the administrative records of policy coverage lagged about 6 months and drought records of the last financial year.

rainfall shock in mandal j affecting the i^{th} child in previous year to the survey. Coverage is a measure of access to NREGS¹⁴ in mandal j . X_j 's are time-varying regressors which include age of the child in months, health inputs, community resources. We saturate equation (1) with all the relevant controls which can change over time and have independent influence on health status like community health infrastructure. The time-invariant regressors like sex of the child, mother's schooling, ethnicity of the household gets washed away in the individual fixed effects specification.

While we do not focus on the independent impact of coverage on households, the key parameter of interest in our analysis is the parameter on the interaction term β_3 , which permits us to analyze the effectiveness of the program in buffering households who were exposed to the drought shocks, for whom we expect it to be all the more beneficial. Precisely, a positive and statistically significant β_3 would indicate that the negative effect of drought exposure on child health status is mitigated by the policy access.

While there is agreement that the make-up of health is highest in early childhood, estimates of mitigation can differ widely by a number of factors, such as severity, duration of the shock exposure, stage of development of the child at the start of malnutrition, gender of the child, household level demographics like education of the mother/caregiver, caste of the household. Duflo (2003) provides some suggestive evidence that the old-age pension had very different effects on child health¹⁵ depending on whether it was received by a woman or by a man. Thus in

¹⁴ We primarily identify coverage from administrative records rather than self-reported measures of participation, hence the analysis is primarily based on the treatment that the households were intended to receive with few follow up robustness checks using actual participation information.

¹⁵ The study found that for girls, living with an eligible household member was associated with an increase of 0.68 standard deviation in height for age.

order to find heterogeneous impact we further estimate equation (1) separately by policy relevant sub-groups.

Investment decisions about the amount of inputs to use may depend on, among other things, the health endowment of the child. It might be that a weak child may attract more attention and inputs from parents in an attempt to ensure his or her survival. Additionally, the overall level and mix of inputs depends on the parental preferences for health, which if not controlled can result in biased estimates. Using the fixed effects in the estimation enables to tackle some of these concerns.

Besides genetic factors, the fixed effects approach also neutralizes additive effects of other unobserved heterogeneity between families, like heterogeneity in terms of disadvantages associated with a location, family structure, traditions, values norms, habits, wealth and household practices that can influence height. However accounting for time varying characteristics across households is more challenging that we try to address by including relevant controls. We discuss the data used for estimation equation (1) in the next section.

1.5 Data and Descriptive Statistics

The current study uses a household panel data set: Young Lives Survey from Andhra Pradesh, India- which is a longitudinal data set collected through household surveys conducted over three waves (2002, 2007 and 2009-10). For our study we use the longitudinal information of children who were aged 6 to 18 months in year 2002. The sample comprises of 20 sub-districts or mandals, the unit of variation in treatment for the current study. The sampling strategy was based on randomly selecting 150 children within 20 clusters or mandals spread across Andhra Pradesh¹⁶. The sample consisted of 7 districts (including 103 villages) from the state to represent

¹⁶ Andhra Pradesh is divided into 23 administrative districts that are further subdivided into 1,125 mandals and 27,000 villages.

the different regions¹⁷ and income levels within the state. Overall attrition by the third round was 2.2%¹⁸ (with attrition rate of 2.3 per cent for the younger cohort) over the eight-year period.

For identifying the variation in access and intensity of NREGS we primarily use the detailed administrative records at the mandal (month-wise mandal-wise records of the average number of days of employment provided, fraction of years the program has been running in an administrative division etc.). We define ‘Coverage’ variable which measures the average number of work days under NREGS per household for a particular mandal in the financial year prior to the survey. We also have self-reported measures for participation in the program at the household level and on whether the household had a job card under the scheme. We use a second definition of coverage-to construct variable ‘NREGS’ which is the first definition but corrected for very low participation (obtained from the household survey data). We declare it to be zero where participation in a mandal was found to be less than 5 percent. This is our preferred measure as it not only captures participation information that are directly contingent to household needs it also implicitly captures the intensity of the program variable (for example- the duration of the program can matter if we believe that the program delivery has improved with time), as typically the average days available under the scheme have increased with time.

While there is no unique, universally-accepted measure of “deficient rainfall”, droughts in most contexts refer to drier-than-average rainfall conditions compared to the long term average of 50 years (IMD, 2002). The drought shock is defined as receiving lower rainfall than the

¹⁷ Andhra Pradesh has three distinct agro-climatic regions: Coastal Andhra, Rayalseema and Telangana. The sampling scheme adopted for Young Lives was designed to identify inter-regional variations with a uniform distribution of sample districts across the three regions to ensure full representation.

¹⁸ Attrition in the Young Lives sample is low in the international comparison with other longitudinal study (Outes and Dercon, 2008)

corresponding long term average for a mandal¹⁹. For the state of Andhra Pradesh-where over 80 per cent of the population depends on agriculture even mild deviation from the expected rainfall during the months of June-September²⁰ can have adverse impacts on the food grain production. Unlike some previous studies which identify drought shocks in YL sample by self reported incidence (Dercon et. al 2011) or constructed from district-wise rainfall, I am able to use the disaggregated annual rainfall records at mandal level²¹, which can be expected to have less measurement error.

Four of the Young Lives sample districts comprising of 11 sub-districts/mandal sites were covered by NREGS in the first phase of implementation in 2005-06, with the addition of four mandal sites in 2007, coinciding with second phase of implementation, and lastly two more mandal sites were included in 2008- coinciding with phase-III of the program expansion. So, essentially, as per our definition of program coverage, in round two of the survey only phase-I districts were ‘treated’ while both phase-II and III sites were not covered. By the third round, all the sample districts were covered, but there exists variation in the program intensity as number of employment days available by mandal was different, which we also include as a further source of variation in the program variable.

We restrict the sample to 4289 observations keeping households that are present in all the survey rounds with complete information on all control variables and exclude potential outlier cases with height-for-age z score beyond the $[-5, +5]$ range. Since, the employment guarantee

¹⁹ We check our results with an alternative measure of drought capturing the fraction of years exposed to drought from birth year till the point in the survey. The estimates on the drought coefficient using the current definition will perhaps give the lower bound of the impact as we did not separate severe droughts, where one can expect the impact would have been even greater.

²⁰ Three-quarters of rainfall is received by the country annually at this time (PACS, 2008).

²¹ Obtained from the Directorate of Economics and Statistics, Government of Andhra Pradesh.

policy is only relevant²² for the rural sector we focus on rural sample comprising 17 mandals and use the urban sample for falsification test.

We include the following time varying observables that can be controlled- the exact age of the child in months at the time of interview, community health infrastructure²³ (Health Facilities) captured by the number of health care units (both government and private hospitals) present in the community (mandal-level). We also check whether inclusion of factors like access to external food supplement as captured by whether child has been a part of supplemental food program in ICDS²⁴ centre/mid-day meal²⁵ that has independent influence on health status makes any difference to our findings.

While identifying drought at the mandal level from administrative records (rather than measuring drought exposure reported at the household-level), we have mitigated the reporting bias and some selection bias (from family-specific unobservables related with exposure variables) however we have also introduced a source of measurement error and caused a potential attenuation bias in the estimates. Even though droughts are categorized as covariate shocks which simultaneously affect households over large geographical areas (in spite of the fact that we do have very disaggregated rainfall data at the mandal-level), they are unlikely to affect all households equally in a given community. Precisely the household-level impact of a drought will

²² It might have some indirect /spillover effects on the urban sample which we include as a falsification test.

²³ There exists variation in terms of health infrastructure across communities which might be related with health outcomes of child or approximating the health awareness factor in a community.

²⁴ Launched in year 1975, Integrated Child Development Scheme (ICDS) supplementary feeding is supposed to provide support to all children 0-6 years old for 300 days in a year (25 days a month).

²⁵ The Midday Meal Scheme is a school meal program in India which started in the 1960s was universalized by 2002. Both of these food supplement programs were universalized across the country much ahead of the NREGS policy implementation and were not associated with the availability of the employment guarantee scheme in a mandal.

depend on the occupation type among household members, availability of alternative irrigation sources, availability of alternative livelihood, access to safety nets, etc.

For approximating household education we construct the variable ‘Primary’ measuring whether the caregiver has completed primary schooling. The ‘Food Supplement’ is a binary variable constructed from self-reported measures that takes value 1 if the child received food under the ICDS²⁶ scheme between round 1 and round 2 or if the child availed mid-day meal scheme between round 2 and round 3 (i.e. when the kids in our sample were of school going age). However we do not primarily include this variable (it might be endogenous) in our main specifications but include it to see if the inclusion changes our result.

We show the descriptive statistics of the key variables in Table 1.1 by phase-wise sites (phase II and III sites have been clubbed together as none of these received the program by the second round). We find that the anthropometric status of children – as measured by height-for-age – deteriorates between the time of birth and 5 years of age for all phases-wise locations (Figure 1.2). We have 66 % of our total rural sample from the phase I locations, which were the only ones to receive the program by the second round of the survey.²⁷

We present the mean height for age score by drought exposure and coverage access in Table 1.2. We find that the mean height for age score is statistically different by exposure to drought among those individuals who did not have coverage (column 1). However this difference is not statistically significant for those who *had access* to coverage (column 2).

On average we see the height-for-age z-scores declined sharply from round 1 to round 2 for all the locations (Figure 1.2). In round 1 of the survey the mean height-for-age z-score in

²⁶ Launched in year 1975, Integrated Child Development Scheme (ICDS) supplementary feeding is supposed to provide support to all children 0-6 years old for 300 days in a year (25 days a month).

²⁷ The phase I mandals got access to coverage by April 2006, phase II mandals by April 2007, and Phase III mandals by April 2008.

phase I mandals was -1.20 (statistically different from that in phase II and III mandals) which substantially went down to -1.84 in round 2 and improved to -1.81 in the third round. For phase-II²⁸, the mean height-for-age z score went down from -1.50 to -1.70, which again went up to -1.66 in the third round. Noteworthy is the fact that compared with other two phases, for phase III sites, which although being higher on the development index, had worse outcomes to start with witnessed decline in mean height-for-age z score between *all* the three rounds (from -1.55 to -1.74 between the first two rounds and then to -1.84 in the third round). These location sites in phase III were the last ones to get the coverage.

Although the difference in mean height-for-age z scores between phase I and the rest of the sites was statistically different in round one of the survey, when we restrict the sample to those who suffered from drought in birth year this difference in mean z-scores between the phases is no longer statistically significant (Figure 1.3). Interestingly when we split the phase I sample²⁹ by drought exposure in birth year (Figure 1.4) we find a very stark difference in mean height for age score between the two groups. The average height for age z score of the children (aged around 1 year) was found to be around 0.4 standard deviations less for the children who were exposed to drought in the year of birth and this difference is statistically significant in the first round. Now this difference is not conditional on the program hence we cannot comment whether it would have been any different in the presence of the policy. However the height for age drops for both of these groups between the first two rounds and the difference between the outcomes of

²⁸ It should be noted that the urban locations from all the districts were dropped from the current analysis, however the calculation of backwardness index on the basis of which coverage was rolled out in a particular district included these locations. Thus, it is not surprising, in spite of being slightly higher in rank in the backwardness index as a district, for the remaining rural sample locations under phase II, the average height-for age was slightly worse off than that of phase-I.

²⁹ The other two phase sites faced drought in birth year, hence we just restrict the sample to phase I sites for analyzing this variation in Figure 1.3.

the two groups are no longer statistically significant from second round onwards. We try to examine if there is any difference based on participation of the program.

Around 32% of the households in phase 1 report to have not participated in the program in round 2. We utilize this variation and compare the child outcomes of the participants with the non-participants (both being exposed to drought in their birth year). So, for phase I locations we restrict the sample to those who were exposed to drought in birth year (Figure 1.5) and try to see if any difference in mean z score exists by participation in the program. We find on average, households that availed the program by the second round (i.e. already had the program for about one year) had higher average height-for-age score than those who did not participate. However the difference is not statistically significant.

In Figure 1.6 we add the trajectory of mean height for age for sample of households who did not face drought in birth year in addition to the graph in Figure 1.5. We find although difference in the average z score (between the sample exposed to drought in birth year versus those who were not) is statistically significant in round 1 it is not so in round 2. Further, the mean z score for the unexposed group was almost the same as the score for individuals exposed to drought in birth year but who participated in the program.

Figure 1.7, Figure 1.8 and Figure 1.9 captures the mean z scores by education of the caregiver, gender of the child and caste groups respectively. We find a statistical significant difference in means of the outcomes by education of the caregiver (where the height-for-age scores of children with caregiver's education below primary schooling was found to be always significantly lower compared to the reference group) and by caste groups (z scores of children from lower caste households were significantly lower for all the rounds) as expected from our intuition. We discuss the regression estimation results in the next section.

1.6. Discussion of the Findings

All regression specifications with height-for-age as outcome variable includes individual fixed effects, and regressions with average stunting percent at the mandal level include mandal fixed effects. We use robust boot strapped standard errors clustered at the level of mandal (treatment level).

Table 1.2.2 shows the regression estimates of drought shock, program access and their interaction on Height-for-Age for individual-fixed effects specifications³⁰. We find while exposure to drought significantly reduces the height-for-age by around 0.373 standard deviations, the significant and positive coefficient of the interaction term indicates that program serves as a significant buffer against these shocks. In order to interpret the magnitude of the effect, we find that for one standard deviation increase in program day increases the height-for-age z-score by around 0.264³¹ standard deviations for those who suffered from drought³², thereby mitigating some of its negative impact.

Based on this estimation we plot the predicted marginal effect of drought exposure (capturing the interaction effects) on height for age score by average number of days under NREGS in Figure 1.10. We find that as the number of days increase under NREGS the marginal impact of drought exposure increases the height for age z score. This provides additional evidence that number of days matter in the buffering role of the program in the mitigating drought

³⁰ For a falsification test we include the urban sample in specification (2) the idea being that the availability of the program in the rural will not have an impact on urban households. However we do not find any statistically significant impact of drought shock on urban and hence cannot check the buffering effect of program.

³¹ Since Coverage is the average number of days we find the magnitude by multiplying the interaction coefficient by the standard deviation of the NREGS days $(.012*22)=.264$ standard deviation increase in height for age .

³² By not distinguishing the different degrees of severity in the drought measure perhaps the estimated impacts are biased downwards. Noteworthy is the fact that 34% of the drought in 2002 were severe droughts, and restricting to that definition would have yielded much higher negative impacts.

impacts.

We present the results of robustness check using the alternative definitions of the program variable in Table 1.2.3. All the four specifications include the individual fixed effects apart from the usual controls of age, health facilities along with the drought exposure, program variable and their corresponding interaction term. Specification (1) uses the average number of days provided(Coverage); specification (2) uses the coverage variable corrected for very low participation (NREGS); specification (3) includes the coverage intensity(Program intensity)-measuring the fraction of years the mandal received the program; specification (4) includes self-reported participation variable (NREGA).

We find the interaction effect using the self-reported participation to be the highest among all of these. Precisely, a one standard deviation increase in program intensity leads to 0.33 standard deviations increase in height for age. From specification (4) we see participation in the program is associated with an increase in the z-score by 0.48 standard deviations for those who exposed to drought. However as stated earlier self-reported participation is more endogenous than the administrative coverage variable hence we mainly focus on the first three specifications.

In Table 1.2.4 we carry out a similar exercise with the outcome variable of average stunting³³ defined at the mandal level. We include ‘Coverage’ in specification (1) and (3) and ‘NREGS’ in specification (2). We find that the average level of stunting increases by around 8% with exposure to drought. The result does not change and is robust to alternative measures used for defining coverage³⁴. We find that a one standard deviation increase in average program days

³³ Stunting is a dummy variable(=1) for Height-for-age less than -2 standard deviations.

³⁴ We also check by including the intensity of the program captured by the fraction of years it has been in place (not reported here).

leads to reduction in stunting by 6%³⁵ for locations exposed to drought. In specification (3) we estimate the same equation as that in specification (1) but for urban sample. Again, we do not find any significant impact of the drought or the program in the urban sample.

We now examine if the effects of mitigation vary by demographic characteristics of the household. In Table 1.2.5 we simply disaggregate the regression results by gender to examine if there is asymmetric burden of shocks on female child. We do not find any significant difference in the estimates by gender.

In Table 1.2.6 we examine the impacts by ethnic/caste groups, as one might expect that the backward caste households faces most of the brunt of shocks. While there is a greater negative impact of drought exposure (reduction in height for age by 0.38 standard deviations) for the backward caste children we find the availability of program is significant in serving as buffer for this group only.

In Table 1.2.7 disaggregating the results by education level of the caregiver we find a strong significant negative impact of drought exposure (reduction in height for age by 0.36 standard deviations) on children when the caregiver's education level is below primary level. The impact of drought although negative is not found to be statistically significant for those kids whose caregivers have finished the primary education. However we find significant mitigating impact of the program across both of these groups.

The findings highlight the extreme vulnerability faced by the rural poor households particularly who have no formal education which further underscores the importance of social protection scheme for these households to counter the negative shocks. Also, when we include the

³⁵ Magnitude is obtained by multiplying the standard deviation with the interaction coefficient (0.003*22).

food supplement variable we find a strong positive and significant impact of the food variable³⁶.

The coefficient of program variable across the specifications although statistically insignificant has a negative sign indicating the possibility of negative selection for participation in the program. It is quite plausible that people who lost jobs/ had a decline in household income joined the program. Also, notable is the fact that when we exclude the fixed effects the OLS results (not reported here) understates the impact of both drought and the mitigation. Although, we find the health facility variable to be positive and significant in the OLS specifications, we find it insignificant with the fixed effects. The estimated coefficient on 'Age' was always found to be negative and significant across all specifications in rural sites signifying worsening of z-score with the age. (Hoddinott 2011) points this is often the case in developing countries where the height for age score typically declines in the first three years and then stabilizes. In our result a one year increase in age decreases height-for-age z-scores by around 0.09 standard deviations in the fixed effects estimation.

While there is no significant difference of the program impact by the gender of the child there is significant difference by the caste and education level of the household members. Hence there is much room which the policy can address by working on ensuring food security issues of these households. Thus to summarize we find evidence that the program helps mitigate recent exposure to shocks, especially for the case of lower educated households and scheduled castes, who are presumably more vulnerable in the face of climatic variability.

Now, in order to examine whether the policy help mitigate past shocks that has accumulated over the years which is particularly relevant for height measure (height being a stock variable reflecting all past inputs into child health including the impact from past shocks) we

³⁶ The estimations including food supplements although shows positive and significant impacts were not reported here as it might be endogenous and also interact with the program variable. However inclusion of food supplement does not alter our main findings.

check the robustness of the current results defining drought in a cumulative manner (specifically capturing the fraction of years the child was exposed to drought from birth till the point in survey).

Table 1.2.8 and Table 1.2.9 present the results for height-for age and average stunting level with the cumulative drought measure. Both the results confirm that cumulative drought has significantly strong negative effect on health outcomes. The interaction term of program and drought in Table 1.2.8 although positive (suggestive of mitigation) is not statistically significant. This implies the program availability is not able to serve as a buffer for correcting cumulative past deficits. The result has crucial implications for insuring vulnerable rural poor households from unforeseen weather shocks given that negative effects of these shocks in early life prove to be irreversible even when a social safety net is available later on in life. The program does only prove to be effective for buffering recent shocks. Hence, taking evidence from our findings it is important to note here that social safety nets available later on life cannot mitigate past deficiencies that carry forward later on life.

1.7. Policy insights and Future work

To discuss our findings in the light of policy insights we find while there is long-run impact of early-life conditions on health several years later, access to coverage helps tackle only for recent shocks but not correct for longer-term past deficiencies. This reconfirms the fact that there is little scope of remediation of correcting past deficiencies which highlights the importance of insuring households against such unforeseen shocks. This has crucial implications in the light of the recent literature that reinstates earlier deficiencies in human capital is very likely to be transferred across generation. A recent study by Hoddinott et al. (2011) finds that individuals who did not suffer growth failure in the first three years of life complete more schooling, score

higher on tests of cognitive skill in adulthood, have better outcomes in the marriage market, earn higher wages and were more likely to be employed in higher-paying jobs. So, as we recognize the critical role of early life conditions prove to have influence on human capital outcomes in long run, there is much room that policies can address in this regard.

Firstly, it has important implications for program design -we find that an increase in 22 working days per household increases height-for-age by around 0.26 standard deviations for those always exposed to recent drought. In terms of commenting on how big is this effect, we can say it is quite substantial: bridging about half the rural-urban gap. Now given that Andhra Pradesh has been one of the better performers in implementation of this program one has to be careful in generalizing this result for other states. While the availability of this longitudinal data was critical to the measurement of program impact over time it would be a difficult to undertake the same exercise for other states due to lack of similar data. Combining the findings with the recent evidence (Dutta et al. 2012) that highlights the extent of unmet demand in the poorer states were higher, special attention needs to be given on correcting that aspect. Noteworthy is the fact that this increase in height for age is quite significant given the children were all around five year old when the program first came in place. The mitigation could have been perhaps higher had it come much earlier in their lives, given the important role of availability of resources in very early childhood.

Secondly, there needs to be special focus on correcting for the lack of child care centre at the worksites that can play a key role in encouraging women participation. This will also account for the reduction in child care time used up in work time for the earned income. Recent studies (Dand et al.2012, Dreze et al. 2007) mention that although the main stated objective of the NREGA is not tied to improving child nutrition, it can reduce childhood malnutrition in a much

effective³⁷ manner through a convergence of nutritional program with provision of crèches³⁸. World Bank report (2011) indicates the program has failed in building assets valuable to the community often due to lack of community participation and absence of sensitization of women's concerns in the project design. All these findings call for correcting the loopholes in program implementation and a rigorous cost-benefit analysis to generate rigorous evidence on the proposed convergence of ICDS with the program.

In the future work we plan to extend and enrich the current analysis by using the available information on percentage of women participation in mandal to further explore the links between women's labor supply and child outcomes examining the path between women's independent income benefiting household nutrition and child health. Additionally it would be interesting to see whether using women participation as an instrument for program access makes any difference to the current estimates. In addition to that, we plan to include the continuous rainfall measure to be able to exploit finer sources of variation to better examine the mitigation impacts of coverage for varying severity of the drought shocks. Finally, the availability of fourth round of this Young Lives panel data would enable us to examine the persistence of the current effects in the adolescence of these children.

³⁷ Allen et al. (2001) mentions combining and converging the services of improved infant feeding, better household access to food, and improved and more accessible sanitation would be a cost effective way in combating undernutrition, (where food, health and care are all problems) than any of these measures taken alone.

³⁸ Few studies including (Khera et al.2009) mention the lack of-almost non-existent- child-care facilities as one of the most important difficulties for women to participate especially those with breastfeeding babies

References

- Alderman, H., J. Hoddinott and B. Kinsey (2006) Long-term Consequences of Early Childhood Malnutrition, *Oxford Economic Papers*, 58.3: 450-74.
- Alderman, H., (2010) Safety nets can help address the risks to nutrition from increasing climate variability, *Journal of Nutrition* 140 (1S-II), 148S–152S.
- Almond, Douglas and Janet Currie (2011) Killing Me Softly: The Fetal Orgins Hypothesis, *Journal of Economic Perspectives*, 25 (3):153–172.
- Allen, L., & Gillespie, S. R. (2001) What works?: A review of the efficacy and effectiveness of nutrition interventions (No. 5). United Nations, Administrative Committee on Coordination, Sub-Committee on Nutrition.
- Azam, Mehtabul (2012) The Impact of Indian Job Guarantee Scheme on Labor Market Outcomes: Evidence from a Natural Experiment, Working paper
- Behrman, Jere R., John Hoddinott, John A. Maluccio, Erica Soler-Hampejsek, Emily L. Braun, J Von, T Teklu and P Webb (1992) Labour-intensive public works for food security in Africa: Past experience and future potential, *International Labour Review*. Vol 131 No.1.
- Berg, E., Bhattacharyya, S., Durgam, R., & Ramachandra, M. (2012) CSAE Working Paper WPS/2012-05.
- Brown, Lynn R., Yisehac Yohannes and Patrick Webb (1994) Rural Labor-Intensive Public Works: Impacts of Participation on Preschooler Nutrition: Evidence from Niger, *American Journal of Agricultural Economics*, Vol. 76, No. 5, Proceedings Issue , 1213-1218.
- Cameron, N., Preece, M. A., & Cole, T. J. (2005). Catch-up growth or regression to the mean? Recovery from stunting revisited. *American Journal of Human Biology*, 17(4), 412-417.
- Carter, M. and J. Maluccio (2003) Social Capital and Coping with Economic Shocks: An Analysis of Stunting of South African Children, *World Development* 31 (7): 1147–1163.
- Cunha, Flavio and James Heckman (2008) Formulating, Identifying and estimating the Technology of Cognitive and Non-Cognitive Skill Formation, *Journal of Human Resource s*43.4: 739-82.
- Currie, J and E Moretti (2007) Biology as Destiny? Short-and Long-Run Determinants of Intergenerational Transmission of Birth Weight, *Journal of Labor Economics* UChicago Press.
- Dand, S., Sundararaman, T., Prasad, V., & Shatrugna, V. (2012) Strategies for Children under Six.
- De Janvry, A., E. Sadoulet, P. Solomon, and R. Vakis (2006) Uninsured Risk and Asset Protection: Can Conditional Cash Transfer Programs Serve as Safety Nets, Social Protection Discussion Paper Series, No. 0604. The World Bank, Washington, D.C

- Dercon, S.(2011) Social protection, efficiency and growth, CSAE Working Paper WPS/2011–17, *Centre for the Study of African Economies*.
- Dercon, S., Park, A., & Singh, A. (2012) School Meals as a Safety Net: An Evaluation of the Midday Meal Scheme in India.
- Deolalikar, A. B., (1996) Child nutritional status and child growth in Kenya: Socioeconomic determinants, *Journal of International Development* 8(3): 375-393.
- Mahendra Dev, S. (2012). Agriculture-nutrition linkages and policies in India, IFPRI Discussion Paper 01184
- Dreze, Jean and Reetika Khera (2009) The battle for employment guarantee, *Frontline* Volume 26 Issue.
- Drèze, J., Holla, R., Garg, S., Sundararaman, T., Prasad, V., & Shatrugna, V. (2007). strategies for children under six. *Economic & Political Weekly*, 87.
- Duflo, E. (2003) Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa. *The World Bank Economic Review*, 17(1), 1-25.
- Dutta, P., R. Murgai, M. Ravallion, D. van de Walle (2012) Does India's Employment Guarantee Scheme Guarantee Employment? World Bank Policy Research Working Paper No. 6003, March.
- Fakuda-Parr, Sakiko, Lawson-Remer, Terra and Randolph, Susan (2009) An Index of Social Rights Fulfillment: Concept and Methodology *Journal of Human Rights* Vol 8, no. 3 , 195-221.
- Elbers, C., J. W. Gunning and B. Kinsey (2007) Growth and Risk: Methodology and Micro Evidence, *World Bank Economic Review* 21: 1-20.
- Fedorov, L., Sahn, D. E. (2005) Socioeconomic Determinants of Children's Health in Russia: A Longitudinal Study. *Economic Development and Cultural Change*, Vol. 53, No. 2, pp. 479-500
- Galab, S., P.P. Reddy and Rozana Himaz (2008) Young Lives Round 2 Survey Report Initial Findings: Andhra Pradesh, India, Oxford: Young Lives.
- Galab, S.,S.Vijay Kumar,P.P.Reddy,Renu Singh and Uma Vennam (2011) The Impact of Growth on Childhood Poverty in Andhra Pradesh: Initial Findings from India Round 3 Survey.
- Gennetian,L,Heather Hill, Andrew London,Leonard Lopoo (2010) Maternal employment and the health of low-income young children, *Journal of Health Economics*, Volume 29, Issue 3, May 2010, 353–363.
- Gilligan and Hoddinott (2006) Is There Persistence in the Impact of Emergency Food Aid? Evidence 15 on Consumption, Food Security, and Assets in Rural Ethiopia *FCND Discussion Paper* 209. IFPRI.

Gilligan, D. O., Hoddinott, J., & Taffesse, A. S. (2009). The impact of Ethiopia's Productive Safety Net Programme and its linkages. *The journal of development studies*, 45(10), 1684-1706.

Gore, P.G.,Thakur Prasad,H.R.Hatwar (2010) Mapping of Drought Areas Over India ,NCC Research Report of IMD,Pune.

Government of India (2008) The National Employment Guarantee Act 2005. Operational Guidelines, Ministry of Rural Development.

Government of India (2011) Census of India: Provisional Population Tables 2011', New Delhi: Ministry of Home Affairs

Government of India (2012) MGNREGA Outcomes for 2010 - 2011. Net nrega http://164.100.12.7/Netnrega/mpr_ht/nregampr_dmu.aspx?flag=1&page1=S& Ministry of Rural Development.

Government of India (2012) Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) 2005, Report to the People, 2nd February 2012, Ministry of Rural Development, Department of Rural Development, Government of India, New Delhi

Hagen-Zanker, Jessica, Ann McCord and Rebecca Holmes with Francesca Booker and Elizabeth Molinari (2011) Systematic Review of the Impact of Employment Guarantee Schemes and Cash Transfers on the Poor ODI, London.

Handa, S and A. Peterman(2012) Is there Catch-Up Growth? Evidence from Three Continents. Working Paper.

Hoddinott, J. and B. Kinsey (2001) Child Growth in the Time of Drought, *Oxford Bulletin of Economics and Statistics* 63(3): 409-36.

Hoddinott, J., J. Behrman, R. Flores, and R. Martorell (2008) The Impact of Nutrition During Early Childhood on Income, Hours Worked, and Wages of Guatemalan Adults, *The Lancet* 371.1: 411-16.

Holmes, R., & Jones, N. (2010). Gender inequality, risk and vulnerability in the rural economy: re-focusing the public works agenda to take account of economic and social risks. Background paper prepared for The State of Food and Agriculture, 11.

Imbert, C and J Papp (2012): Equilibrium Distributional Impacts of Government. Employment Programs: Evidence from India's Employment Guarantee, Paris School of Economics, Working Paper.

Indian Meteorological Department (2002) South-West Monsoon 2002: End-of-Season Report New Delhi: Government of India.

Jacoby, H. G. and Skoufias, E. (1997) Risk, Financial Markets, and Human Capital in a Developing Country, *Review of Economic Studies*, vol. 64, no. 3, 311-335.

- Johnson,R, M.E. Corcoran(2003) The road to economic self-sufficiency: job quality and job transition patterns after welfare reform, *Journal of Policy Analysis and Management*, 22 (4), 615–539.
- Khera, Reetika and Nandini Nayak (2009) Women workers and perceptions of the National Rural Employment Guarantee Act in India, Paper presented at the FAO-IFAD-ILO Workshop on Gaps, trends and current research in gender dimensions of agricultural and rural employment.
- Reetika Khera and Nandini Nayak (2009) Frontline cover story” Battle for Work” - “What works against women”.
- Kumar, R.H. et al. (2005) Diet and nutritional status of the population in the severely drought affected areas of Gujarat, *Journal of Human Ecology*. 18(4), 319–326.
- Lanjouw, Peter and Martin Ravallion (1999) Benefit Incidence and the Timing of Program Capture”, *World Bank Economic Review* Vol 13 No. 2 ,257-274.
- Maccini, Sharon and Dean Yang, (2009) Under the Weather: Health, Schooling and Economic Consequences of Early-Life Rainfall, *American Economic Review*, 99(3), 1006-1026.
- Mani, S., (2008) Is there Complete, Partial, or No Recovery from Childhood Malnutrition? Empirical Evidence from Indonesia, Fordham Economics Discussion Paper Series dp2008-19, Fordham University, Department of Economics.
- Martorell, R., Khan, L. K., Schroeder, D. G.(1994) Reversibility of stunting: epidemiological findings in children from developing countries, *European journal of clinical nutrition*;48 Suppl 1:S45-57.
- Martorell, R. (1999) The nature of child malnutrition and it's long-term implications, *Food and Nutrition Bulletin*, 20(3): 288-292.
- National Family Health Survey-NFHS(2006), http://www.nfhsindia.org/nfhs3_national_report.
- Outes-Leon, I. and Dercon, S., (2008) Survey Attrition and Attrition Bias in Young Lives, Young Lives Technical Note 5, Oxford: Young Lives
- PACS-CSO (Poorest Area Civil Society – Civil Society Organization)(2007) Status of NREGA implementation: Grassroots learning and ways forward. 2nd monitoring report (April 2006 to March 2007). Delhi, India: Poorest Area Civil Society (PACS) Program.
- Rao.P (2008) Climate change and agriculture over India, AICRP on *Agrometeorology*,116.
- Ravallion, M (1991) Reaching the Poor through Rural Public Employment: Arguments, Evidence and Lessons from South Asia, *The World Bank Research Observer*.
- Ravallion, M,Datt and Chaudhuri (1993) “Does Maharashtra's Employment Guarantee Scheme Guarantee Employment? Effects of the 1988 Wage Increase.” *Economic Development and Cultural Change*, Vol. 41, No. 2, (Jan., 1993), 251-275.

- Reddy, D.N., Rukmini Tankha, C. Upendranadh and Alakh N. Sharma (2010) National Rural Employment Guarantee as Social Protection. *IDS Bulletin* Volume 41 Number 4 July 2010, 63-76.
- Sainath, P. (2007) Nearly 1.5 lakh Suicides in 1997-2005, *The Hindu*, 11 November.
- Scott, E. K. Edin, A.S. London, R.J. Kissane (2004) Unstable work, unstable income: Implications for family well-being in the era of time-limited welfare, *Journal of Poverty*, 8 (1) (2004), 61–88.
- Schroeder D.G., Martorell R., Rivera J.A., Ruel, M.T., Habicht J-P., (1995) Age differences in the impact of nutritional supplementation on growth, *Journal of Nutrition* 1995;125(4 suppl):1051S1051
- Strauss, J., and Thomas, D. (2008) Health over the life course, in T.P. Schultz and J. Strauss (eds.), *Handbook of Development Economics*, Volume 4, Amsterdam: North Holland Press.
- Smith, L., Ramakrishnan, U., Haddad, L., Martorell, R., & Ndiaye, A. (2001) The importance of women's status for child nutrition in developing countries Policy Report. Washington, DC: International Food Policy Research Institute.
- Subbarao, Kalanidhi, et al. (2012) Public Works as a Safety Net: Design, Evidence, and Implementation, World Bank Publications
- Unicef (2009) Tracking progress of child and maternal nutrition: A survival development priority
- Uppal V. (2009) Is the NREGS a Safety Net for Children? *Young Lives Student Paper*.
- Van den Berg, G., M. Lindeboom, and F. Portrait (2007). Long-run Longevity Effects of a Nutritional Shock Early in Life: The Dutch Potato Famine of 1984-1847. Unpublished manuscript, IZA Discussion Paper 3123.
- Vij, N. (2011) Collaborative Governance: Analysing Social Audits in MGNREGA in India *IDS Bulletin*, 42: 28–34. doi: 10.1111/j.1759-5436.2011.00269.x
- World Bank (2011) Social Protection for a changing India, Washington DC, USA, World Bank, <http://documents.worldbank.org/curated/en/2011/01/14087371/social-protection-changing-india-vol-1-2-executive-summary>
- Yamano T., H. Alderman and L. Christiaensen (2005) Child Growth, Shocks, and Food Aid in Rural Ethiopia, *American Journal of Agricultural Economics* 87(2): 273-288. 17
- Zimmerman L. (2012) Labor market impacts for a large scale public works program: Evidence for the Indian Employment Guarantee Scheme, IZA Discussion paper No. 6858.

Table 1.1: Descriptive Statistics

Variable	Phase I		Phase II and III	
	Mean	Std. Dev.	Mean	Std. Dev.
<i>Outcome Variables</i>				
Height-for-age	-1.62	1.24	-1.63	1.09
Stunting	0.38	0.12	0.36	0.10
<i>Measures for NREGS</i>				
Coverage (Average Days)	26.77	22.41	13.99	20.92
Participation Percent	0.44	0.33	0.22	0.31
NREGS	26.77	22.41	13.26	21.04
<i>Measures for Drought Shocks</i>				
Drought	0.56	0.50	0.67	0.47
Cumulated Drought	0.45	0.25	0.65	0.17
<i>Child Level Variables</i>				
Food Supplement	0.43	0.49	0.62	0.49
Age	4.82	2.88	4.84	2.90
Male	0.53	0.50	0.52	0.50
<i>Household Characteristics</i>				
Primary Education of Household Head	0.25	0.43	0.54	0.49
Caste	0.16	0.37	0.10	0.30
<i>Community Characteristics</i>				
Health Facilities	1.88	1.18	3.63	1.23
Observations N=4289	2831		1458	

Note: (i) Coverage represents the average number of days available for the mandal in the last financial year, obtained from administrative records.

(ii) Participation percent is constructed from the self reported measure of participation in the program.

(iii) 'NREGS' represents the Coverage variable corrected for low participation using self-reports.

(iv) Drought is dummy of receiving less than the long term average rainfall at mandal in the year prior to survey.

(v) 'Cumulated Drought' is the fraction of years of having 'Drought' cumulated from birth year.

(vi) Food Supplement is dummy for whether child has been a part of supplemental food program in ICDS centre/mid-day meal

(vii) Health Facilities are the number of health care units (both government and private hospitals) present in the community (mandal-level)

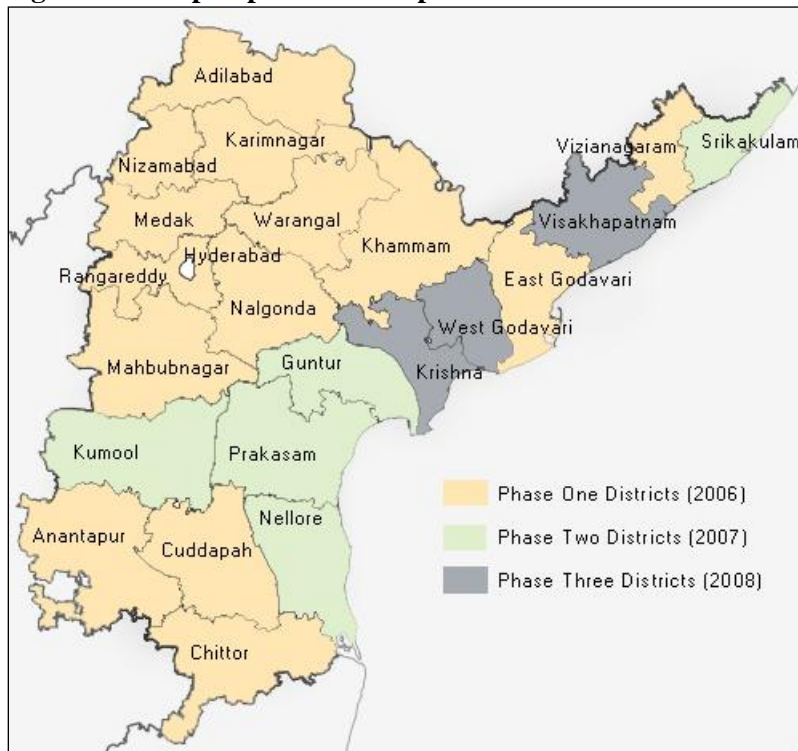
Table 1.2: Comparison of mean Height for age scores by program access and Drought

	Coverage=0	Coverage =1
Drought=0	-1.237 (0.050)	-1.849 (0.032)
Drought =1	-1.487 (0.042)	-1.778 (0.024)
Difference	0.2499	-0.070
p-value	0.0001	0.9591
N	1803	2486

Note: Standard errors in parentheses

- (i) Coverage is a dummy for program availability obtained from administrative records.
- (ii) Drought is dummy of receiving less than the long term average rainfall at mandal.

Figure 1.1: Map of phase-wise expansion of NREGS across Young Lives Sample



Index for Figure 1.1: Phase-wise Coverage across sample districts in Andhra Pradesh

Phase - I	Phase - II	Phase - III
VIZIANAGRAM	EAST GODAVARI	WEST GODAVARI
CHITTOOR	GUNTUR	KRISHNA
CUDAPPAH	KURNOOL	VISHAKHAPATNAM
ANANTPUR	NELLORE	
MAHBUBNAGAR	PRAKASAM	
MEDAK	SRIKAKULAM	
RANGA REDDY		
NIZAMABAD		
WARRANGAL		
ADILABAD		
KARIMNAGAR		
KHAMMAM		
NALGONDA		

*The colored districts are the sample ones from the current survey.

Figure 1.2: Average Height-for-Age by Round and Phase

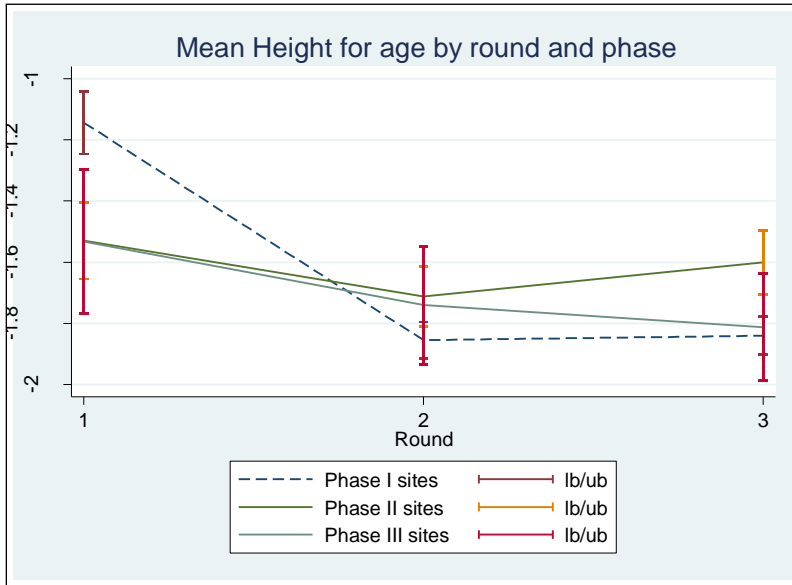


Figure 1.3: Average Height-for-Age by Round and Phase for exposed to drought in birth year

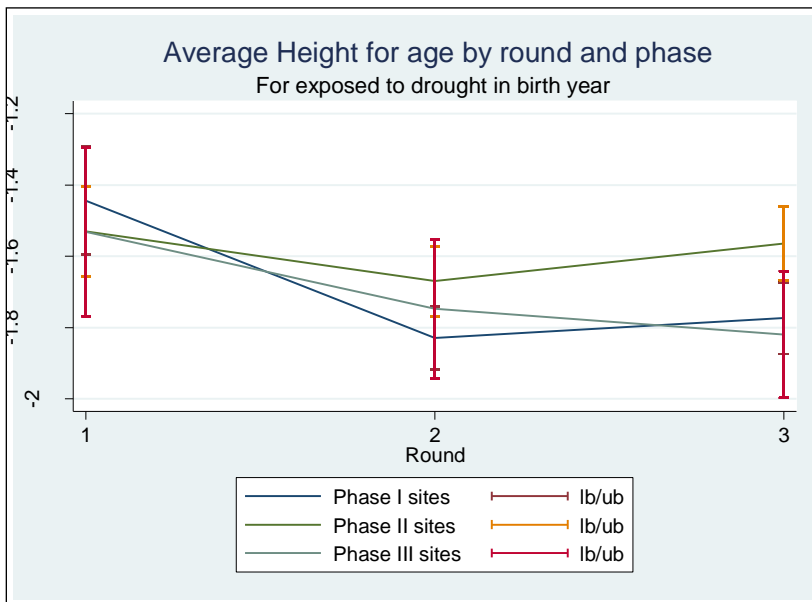


Figure 1.4: Average Height-for-Age by Round and exposure to drought in birth year

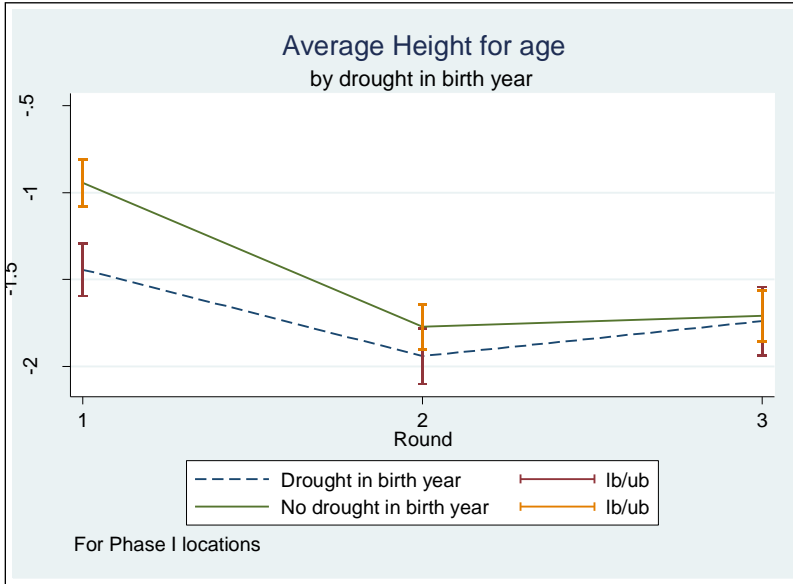


Figure 1.5: Average Height-for-Age by Program participation for exposed to drought in birth year

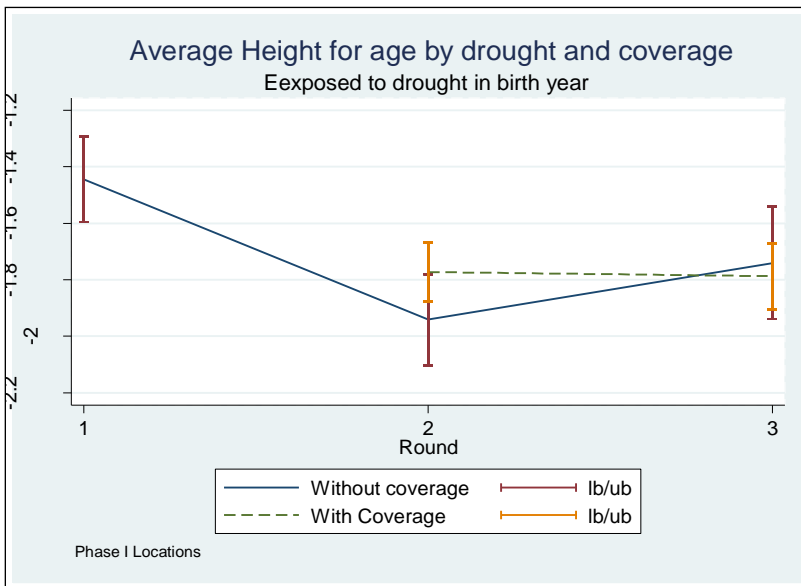


Figure 1.6: Average Height-for-Age by Program participation and exposure to drought in birth year (Phase I sites)

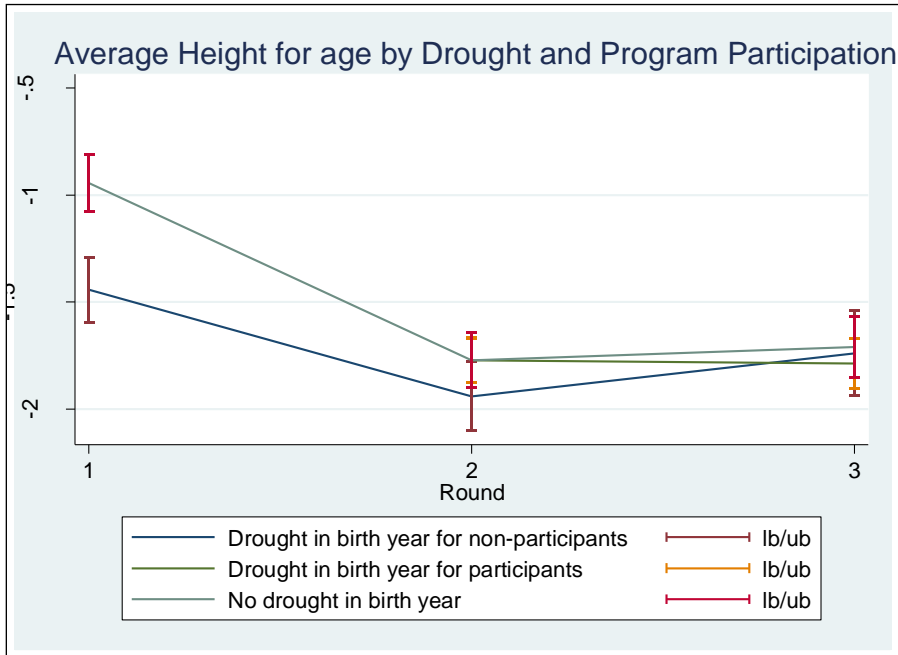


Figure 1.7: Average Height-for-Age by Caregiver's Education

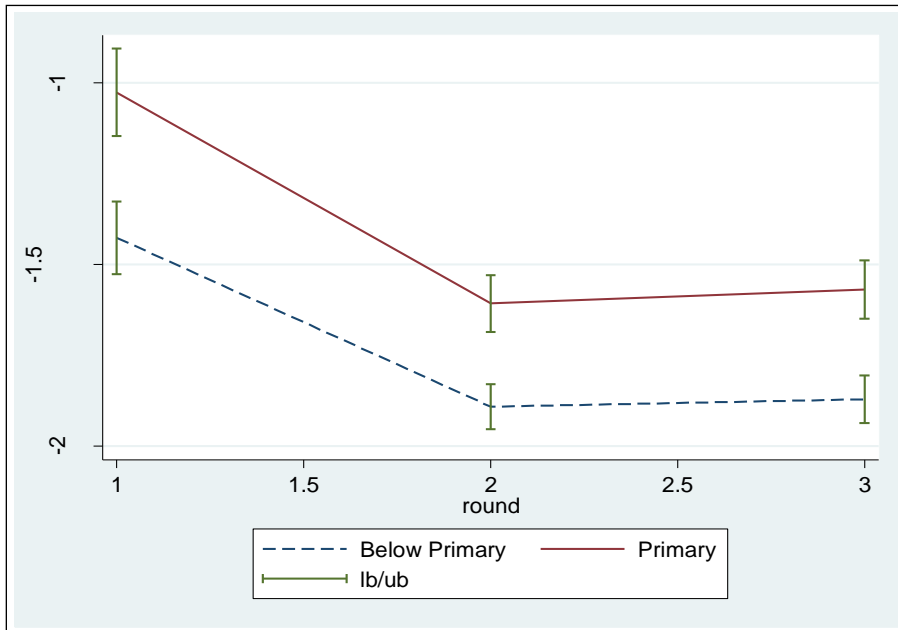


Figure 1.8: Average Height-for-Age by Gender

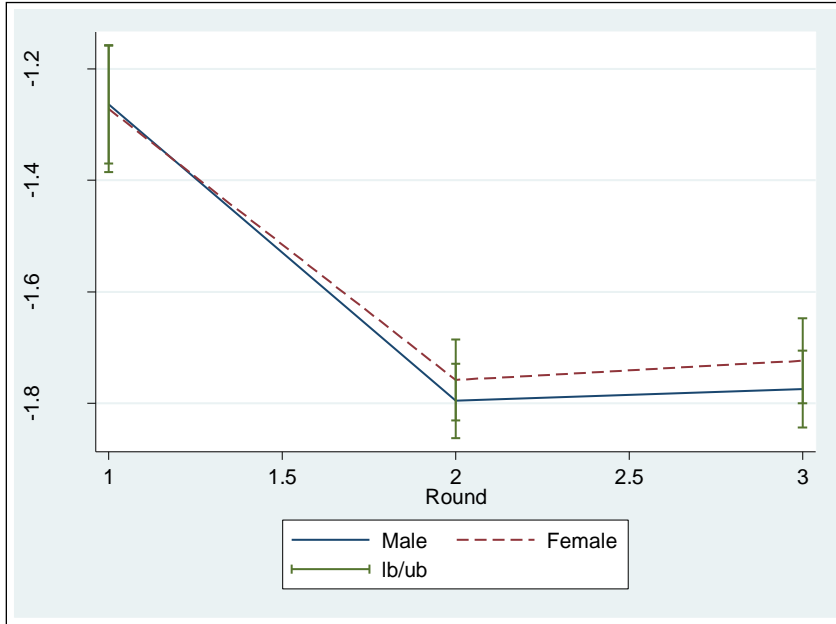


Figure 1.9: Average Height-for-Age by Caste

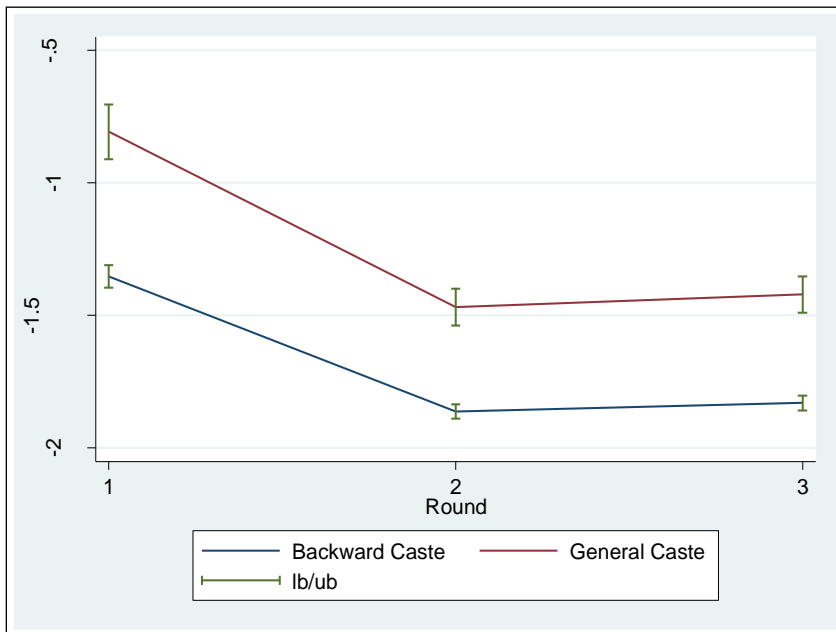


Table 1.2.2: Estimation of Height For Age by Coverage and Drought
Dependent Variable: Height For Age

	(1) Rural	(2) Urban
Drought	-0.373*** (0.132)	0.0322 (0.257)
Coverage	-0.00696 (0.00586)	-0.00593 (0.00887)
Drought*Coverage	0.0127*** (0.00467)	0.00468 (0.00782)
Health Facility	0.0692 (0.0873)	0.106 (0.154)
Age	-0.0851*** (0.0255)	-0.0201 (0.0306)
Observations	4289	1376

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

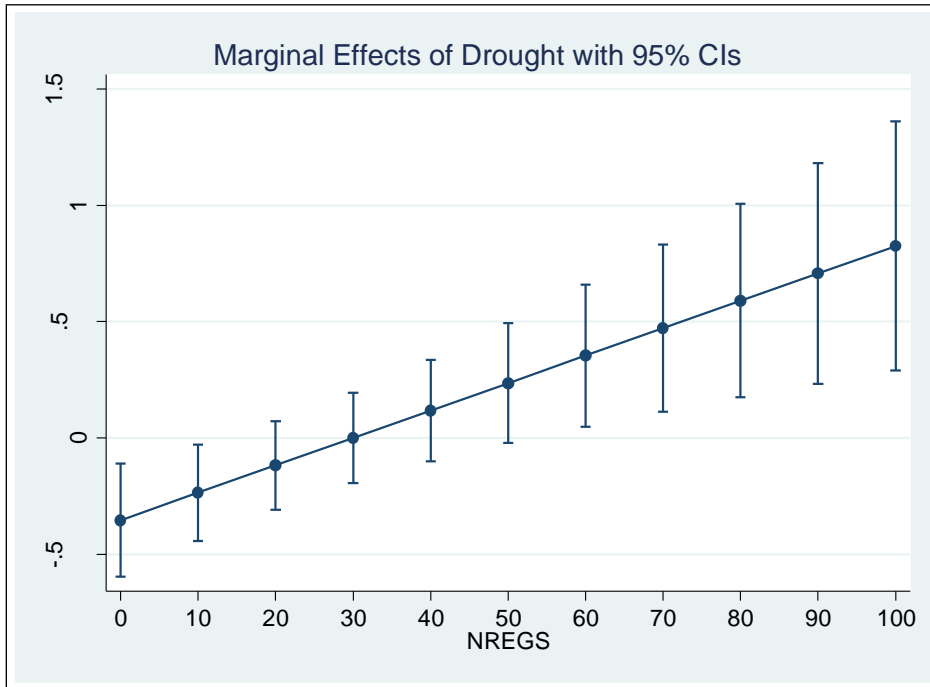
a) HAZ indicates Height for Age, adjusted for both Age and Sex

b) Coverage is average number of days available under the program in the mandal

c) Drought is defined as receiving less rainfall than the long term average at mandal in the year prior to survey

d) All specifications include individual fixed effects

Figure 1.10: Marginal impact of drought shock on height-for-age by NREGS days



Note: (i) NREGS is average number of days available under the program in the mandal
(ii) Linear prediction based on estimation results from specification (1) in Table 1.2.2

Table 1.2.3: Estimation of Interaction effects
 Dependent Variable: Height For Age

	(1)	(2)	(3)	(4)
Interaction variables	NREGS (Avg days)	Corrected NREGS	Program Intensity	NREGA (participation)
Drought	-0.373 ^{***}	-0.369 ^{***}	-0.452 ^{***}	-0.245 ^{**}
	(0.144)	(0.134)	(0.111)	(0.115)
Drought*NREGS	0.0122 ^{***}			
	(0.00470)			
Drought*Corrected		0.0120 ^{***}		
		(0.00442)		
Drought *Prog.Inten			1.121 ^{***}	
			(0.260)	
Drought*NREGA				0.480 ^{***}
				(0.154)
Observations	4289	4289	4289	4289

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses:

* p < 0.10, ** p < 0.05, *** p < 0.01

a) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

b) Specifications include individual fixed effects

c) NREGS is Coverage (Average days per household under the program) corrected for low participation

d) Program intensity measures the fraction of years the mandal received the program;

e)NREGA is a dummy constructed from self-reported participation.

f) All specifications include individual fixed effects, respective program variable, age & health facility

Table 1.2.4: Estimation of Stunting by Drought and Coverage
Dependent Variable: Stunting

	(1) Rural	(2) Rural	(3) Urban
Drought	0.0821** (0.0349)	0.0785** (0.0352)	-0.0292 (0.0439)
Coverage	0.00238** (0.00117)		0.000236 (0.00155)
Drought*Coverage	-0.00341*** (0.000843)		0.0000705 (0.00128)
Health Facility	-0.0116 (0.0284)	-0.0113 (0.0315)	-0.0222 (0.0258)
Age	0.0166** (0.00777)	0.0166** (0.00697)	0.00546 (0.00714)
NREGS		0.00233** (0.000921)	
Drought*NREGS		-0.00333*** (0.000810)	
Observations	4289	4289	1376

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses:

* p < 0.10, ** p < 0.05, *** p < 0.01

a) Dependent variable stunting is dummy variable, takes 1 if Height-for-age < -2

b) Coverage is Average number of Days available under NREGA in the mandal

c) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

d) Specifications include mandal(sub-district) fixed effects

e) NREGS is Coverage (Average days per household under the program)corrected for participation

f) All specifications include individual fixed effects

Table 1.2.5: Estimation of Height For Age by Gender

	(1) Male	(2) Female
Drought	-0.384*** (0.137)	-0.353*** (0.121)
NREGS	-0.00876* (0.00453)	-0.00428 (0.00368)
Drought*NREGS	0.0133*** (0.00358)	0.0114*** (0.00382)
Health Facility	0.0707 (0.115)	0.0689 (0.0928)
Age	-0.0807*** (0.0297)	-0.0969*** (0.0233)
Observations	2272	2017

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses

Note: * p < 0.10, ** p < 0.05, *** p < 0.01

a) HAZ indicates Height for Age, adjusted for both Age and Sex

b) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

c) All specifications include child fixed effects

d) NREGS is Coverage (Average days per household under the program) corrected for participation

e) All specifications include individual fixed effects

Table 1.2.6: Estimation of Height For Age by Caste

	(1) General Caste	(2) Backward Caste
Drought	-0.277* (0.156)	-0.380*** (0.145)
NREGS	-0.00517 (0.00790)	-0.00679 (0.00519)
Drought*NREGS	0.00960 (0.00639)	0.0127*** (0.00390)
Health Facility	0.126 (0.148)	0.0678 (0.0692)
Age	-0.0957*** (0.0336)	-0.0871*** (0.0250)
Observations	600	3689

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses

Note: * p < 0.10, ** p < 0.05, *** p < 0.01

a) HAZ indicates Height for Age, adjusted for both Age and Sex

b) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

c) All specifications include child fixed effects

d) NREGS is Coverage (Average days per household under the program) corrected for participation

e) All specifications include individual fixed effects

Table 1.2.7: Estimation of Height For Age by Caregiver’s Education Level

	(1) Primary & Above	(2) Below Primary
Drought	-0.372 (0.242)	-0.365*** (0.132)
Coverage	-0.0118 (0.00808)	-0.00566 (0.00510)
Drought*Coverage	0.0177** (0.00726)	0.0110*** (0.00350)
Health Facility	0.0434 (0.114)	0.0863 (0.0940)
Age	-0.0756** (0.0368)	-0.0911*** (0.0274)
Observations	1229	3057

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses

Note:* p < 0.10, ** p < 0.05, *** p < 0.01

a) HAZ indicates Height for Age, adjusted for both Age and Sex

b) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

c) All specifications include child fixed effects

d) NREGS is Coverage (Average days per household under the program)corrected for participation

e) All specifications include individual fixed effects

Table 1.2.8: Estimation of Height For Age by Coverage and Cumulative Drought

Dependent Variable: Height For Age	
CD	-0.975*** (0.323)
Coverage	-0.00700 (0.0113)
CD*Coverage	0.0118 (0.0208)
Health Facility	0.00765 (0.159)
Age	-0.0627*** (0.0224)
Observations	4289

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

a) HAZ indicates Height for Age, adjusted for both Age and Sex

b) Coverage is Average number of Days available under NREGA in the mandal

c) CD =Cumulated Drought is a fraction of years having drought at mandal level cumulated from birth year

d) All specifications include individual fixed effects

Table 1.2.9: Estimation of Stunting by Cumulative Drought and Coverage

Dependent Variable: Stunting	(1)	(2)
CD	0.246*** (0.0775)	
CD*Coverage	-0.00422 (0.00430)	
Drought		0.0780** (0.0319)
Drought*Coverage		-0.00325*** (0.000913)
Observations	4289	4289

Robust boot-strapped Standard errors (clustered at the mandal) in parentheses:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

a) Dependent variable stunting is dummy variable, takes 1 if Height-for-age < -2

b) Coverage is Average number of Days available under NREGA in the mandal

c) Drought is receiving less than the long term average rainfall at mandal in the year prior to survey

d) CD=Cumulated Drought is a fraction of years receiving less than the long term average rainfall at mandal cumulated from birth

e) All specifications include individual fixed effects

Chapter 2

Reporting Heterogeneity in Health Status

A study across Population Sub-groups in India Using Vignettes

Abstract

Self-reported health is a widely used proxy in modeling health as a determinant in economic decisions, in the evaluation of health status for individuals, and often important for evaluation of social policies. However the likely presence of non-random measurement error in self-assessed health response by socio-economic and demographic characteristics can potentially bias the measurement thus making interpersonal comparisons problematic. This paper examines the pattern of reporting bias in self reported health data across population subgroups using an unique data from the World Health Survey (WHS)-SAGE survey (wave 1) from India, that has self-reported assessments of health linked to anchoring vignettes as well as objective measures like measured anthropometrics and performance tests on a range of different domains of health. The ordered probit estimation analysis for vignettes responses reveals strong systematic reporting bias with respect to level of development in community, gender, age and sector. Controlling for a battery of objective health measures, we implicitly test the assumption of ‘response consistency’ in vignettes and confirm its validity by finding the presence of similar systematic bias in self-reported health responses across the sub-groups. Further examination of reporting bias by exploiting the individual fixed effects reveals that substantial variation in self-reported health remains unexplained even after controlling for the usual covariates. Thus the results seem to suggest that systematic differences in self-reported health response needs to be accounted for

while making inter group comparisons valid and lends support to the use of the vignette technique for identifying this bias.

Keywords: Self-assessed health; vignettes approach; measurement error; response consistency

2.1 Introduction

Empirical research modeling health as a determinant in economic decisions such as work and retirement, utilization of health services and analysis of economic consequences of ill health typically relies on some form of subjective health measure (Johnston et al. 2009). One of the most widely used measures in this regard is self assessed health (SAH) , which is convenient¹ and informative instrument often shown to be correlated with actual health, mortality, morbidity and health access(Rohrer 2009²). Most studies using data from developing countries focus on measures of self-rated health, nutritional status, activities of daily living, presence or absence of health conditions, and utilization of care, that are often self-reported and for which the validation data is hard to obtain (Currie et. al 1999).

Health and morbidity profile based on National level household surveys like the National Sample Survey in India are typically used to study the utilization of public and private health services by population subgroups (Mishra 2004). Notably it is the primary source of health information that has been extensively used for policy design. An individual is typically asked to indicate whether his health status is excellent, good, fair or poor. Now, any variation in reported health status can come from the following possible sources: variation related to differences in true (latent) health, and/or variation in reporting which is driven by the respondent's personal characteristics. Hence, if health perceptions are systematically correlated with socioeconomic characteristics such as income and exposure to health care systems, self-assessed health status can be misleading. Strauss and Thomas (2007) mention that self reported health measures are

¹ The use of reported health state/ morbidity indicators in health surveys has been often justified because of the difficulties involved in collecting objective and other diagnostic information, which requires rigorous standardization and has greater costs.

² Gives a comprehensive review of policy action at community level that relied on self-reported health measures.

potentially measured with error. This measure has the disadvantage that people may perceive health differently so that 'good health' might not mean the same thing to all people.

Although SAH measure is widely used in empirical research, for a given true but unobserved health state, if survey respondents report their health differently depending on certain characteristics like conceptions of general health, utilization of health services, expectations for own health, financial incentives to report ill health, comprehension of the survey questions, measurement error in SAH is no longer random. As perceived health may vary systematically by population sub-groups even for same level of latent health, its validity has been challenged in the recent literature (Sen 1993, Currie et. al 1999, Strauss et. al 2007, Schultz et al 2008) as it potentially induces biases in estimates thus making statistical inferences on the SAH data problematic. However there has been no formal testing of systematic reporting bias in self-reported health within a developing country, where one can expect this measurement error to be greater.

Antman et al (2006); Escobal et al.(2008) points a number of reasons to in developing country settings, for which validation data are not readily available. In particular, the literacy level of the general population is lower and health awareness may be lower. This becomes more problematic as self report is often the only source of information on health status in case of developing countries.

Bound (2001) highlights that wrong assumption of measurement error in a given variable to be "classical"³ can introduce serious biases in estimates leading to simple attenuation to misattributing relationships that are not present in the error free data. Furthermore, the study points out that standard methods for correcting for measurement error bias, such as instrumental

³ where measurement error is independent of the true level of that variable and all other variables in the model and measurement error in other variables

variables estimation, are valid only when errors are classical in nature and the underlying model is linear, but not, in general, otherwise.

One of the ways to examine systematic measurement error in self-reported health is to formalize the problem of heterogeneous reporting behavior and to formulate tests for its occurrence in the context of subjective health information. In order to correct for systematic differences in reporting heterogeneity across sub-populations, a proposed solution to this measurement error problem is to anchor an individual's self assessed response on her rating of a vignette description of a hypothetical situation that is fixed for all respondents (King et. al 2004; Bago d'Uva et. al 2011). The idea is based on the underlying assumption that since a vignette depicts a fixed level of latent health, variation in its rating would identify systematic reporting bias, which can then be adjusted in the individual's subjective assessment of her own situation.

Anchoring vignettes have been proposed as a solution to this problem, since they permit statistical adjustment for rating style, and thus enable valid intergroup comparisons. However the validity of the vignette approach relies on two important assumptions viz. "vignette equivalence" (requires that all individuals perceive the vignette description as corresponding to a given state of the same underlying construct) and "response consistency" which implies that individuals use the same response categories for their subjective assessment (e.g. of own health) as the categories used for the hypothetical scenarios presented to them in vignettes (Bago d'Uva 2009). This assumption will not hold if there are strategic influences on the reporting of the individual's own situation that are absent from evaluation of the vignette (Bago d'Uva 2011). If this did not hold, then information from the vignette responses cannot be used in identifying, and thus correcting for, the reporting heterogeneity.

While in recent studies this method has been used to correct for systematic reporting bias in some developed country settings very few such attempts have been done for the case of less

developed countries, where measurement error in survey data has been increasingly acknowledged in empirical studies (Strauss and Thomas 2007). Currie et al (1999) suggests that estimates of the effects of health on labor market activity may be very sensitive to the measure of health used, and to the way in which the estimation procedure takes account of potential measurement error. Moreover, there is a serious concern when the error in measurement is not random even after controlling for the observable socio-economic characteristics and thus can lead to a bias similar to "ability bias"⁴ in standard human capital models. Thus, measurement error in such self-reported health variables may represent a source of significant bias in models used to explain work behavior.

The paper first tries to present a framework for individual reporting behavior which enables us to formally test the existence of systematic measurement error across socio-demographic sub-groups in a developing country setting using two different approaches. Second, we examine what part of this reporting bias cannot be explained even after controlling for the socio economic characteristics.

For the first objective we examine the nature of reporting biases using vignettes responses across different health domains and then check the validity of this approach by implicitly testing the 'response consistency' assumption. Essentially we compare the pattern of reporting bias in self reported health response after controlling for their 'objective' counterparts from the same health domain, permitting us to identify reporting effects by socio-demographic covariates. For the second objective we tease out the individual level variation in reporting using repeated ratings from the same individual across different vignettes and examine how much of this variation can be explained by the individual's socio-economic characteristics and what part

⁴ For instance, if healthier individuals are likely to get more education, then failure to control for health in a wage equation will result in over-estimates of the effects of education.

still remains unaccounted for. This exercise is feasible by the unique set up of the data in our analysis which has information for the same individual on vignettes rating, self-reported as well as objective health measures on the same health domain.

This study is be important in finding out the nature of biases in an existing nationally representative survey data from a developing country setting. One of the very first papers Bago d'uva (2008) to test for systematic differences in reporting behavior across developing countries using a pilot data (which was not nationally representative) from Indonesia, India⁵ and China rejected reporting homogeneity by different educational groups. However their study did not include any analysis of either objective (biomarkers) or subjective (reported) self health status which my study is able to include to cross-validate the results obtained from the vignette approach. In this regard it provides a methodological contribution to check the validity of response consistency in vignettes approach which has been debated in the recent literature. It has been argued that individuals may use different thresholds for rating vignette questions as opposed to rating self-reported health questions. Moreover studying the interstate variations within a country was beyond the scope of their study which the present study aims to include to examine the extent of reporting bias across policy relevant subgroups within a country.

The paper is organized as follows. In the next section, a brief literature review is presented followed by the empirical model in Section III. Section IV presents the description of the data along with descriptive statistics. In Section V, the main results are discussed followed by some robustness checks. Section VI concludes the discussion along with policy implications and future work.

⁵ for India only a pilot data from Andhra Pradesh was analyzed in her paper

2.2 Literature Review

Bound et al.(2001) points out that reporting heterogeneity need not be a major concern provided that it is random (the “classical” measurement error case), although it can lead to attenuation bias resulting from the same. As Currie (1999) mentions the main problem with self-reported measures is not that they are not strongly correlated with underlying health status, rather, the problem is that the measurement error is unlikely to be random.

Schultz et al (2008) points that interpretation of evidence that relies on self-reports will be problematic to the extent that those indicators reflect not only true health status but other influences that are systematically related to outcomes of interest in specific models. For instance, if higher wage earners are more likely to access health care services and, because of that, are more likely to report their ill-health, then it will be very difficult to interpret the relationship between wages and self-assessed health status.

Differences in health measures derived from self-reported and more objective indicators are suggestive of systematic variation in reporting behavior (Bago d’uva 2008). A number of papers including Sen (1993, 2002) draws instances from developing countries, where reported illnesses or morbidities indicate that children in the poorest households are the healthiest. Noteworthy is the fact that the state of Kerala (with one of the lowest levels of mortality among Indian states) has consistently reported the highest morbidity rate(approximately three times the all-India average) in three successive rounds of nationally represented survey NSS, whereas in contrast, Bihar -with one of the highest mortality rates reported the lowest morbidity. Now it remains to be examined systematically how much of this can be attributed to perception bias and how much can be explained by survivorship burden of disease. Sen (2002) attributed this discrepancy to a perception bias; that people from states with more education and greater access to health and medical facilities are in a better position to assess their own health than people from

disadvantaged states. Banerjee et al., (2004) mentions that sick individuals in a poor disease endemic area, with limited health access or opportunities for medical treatment may report being in good health because some type of illnesses may be perceived as ‘normal’ phenomena due to their prolonged, widespread occurrence in the area, where people might be adapted to the sickness that they experience.

Using data from the National Health and Nutrition Examination Survey (NHANES) Strauss and Thomas (1996) observe that the gap between maternal reports and measurements of child height is smaller among higher income and better educated mothers and the gaps are smaller among older children. They attribute this finding to the likely differences in the frequency with which children were measured, and argue that mothers of higher socioeconomic status (SES) were more likely visit health centers (where measurements are taken) than women of lower SES.

Van Doorslaer and Jones (2003) analyze differences in reporting that may be influenced by socioeconomic characteristics such as age, gender, education, individual experience with illness and the health care system. They find sub-groups of the population systematically use different thresholds in classifying their health into a categorical measure. Individuals from different population sub-groups are likely to interpret the SAH question within their own specific context and thus use different reference points when asked to respond to the same question (Lindeboom & van Doorslaer, 2004). Baron-Epel et. al (2001) showed that higher educated people tend to assess their health in an optimistic way, even when they have common characteristics such as nationality and religion. Gerdtham et. al(2001) using Swedish micro-data, found SAH to be higher for higher income class, the highly educated and the married.

With respect to the subjective dimension of SAH, Krause et. al (1994) found that people of different age groups tend to think about different aspects of their health when making evaluations. The study found that people with the same ‘true health’ may end up reporting

different levels of SAH depending on their age. Schultz et al.(2008) mentions some illnesses such as blindness, ringworms or malaria may be perceived as normal phenomena due to their prolonged, widespread occurrence in a disease prone area without health access, where individuals may not see themselves as particularly unhealthy.

While various techniques have been proposed for achieving comparable response scales across groups, recent reviews (Murray et. al 2002) indicate anchoring vignettes as “the most promising” of available strategies. Anchoring vignettes, in short, reveal how groups may differ in their use of response categories, i.e., in where along the health spectrum individuals locate thresholds between the ordered categories. Although it is becoming popular however, thus far anchoring vignettes have not been applied to the general self-rated health question (Prokopczyk 2012), despite the widespread use of self reported health and clear indications of measurement bias in the self reported data. Also, the assumption of response consistency has been debated in the recent literature (Bago d’Uva et. al 2011; Van Soest et. al 2011) and it has not been tested in a developing country setting thus far. Further there is no systematic evidence on how much of this bias remains unaccounted for even after including the typical SES variables in a regression. The next section of the paper chalks out the empirical strategy for this.

2.3 Empirical Strategy

In the light of the empirical literature discussed so far, in the current analysis we test whether sub-groups of the population systematically use different thresholds in classifying their health into a categorical measure. In order to test the existence of systematic measurement error in the SAH across population subgroups we first estimate the ordered probit model for the vignettes responses and try to identify the reporting biases across the covariates. The first

approach of our empirical strategy closely follows the model of King (2004) with some modifications.

Let H_i^v be the reported ordered health status (with options ‘very good’=1, ‘good’=2, ‘moderate’=3, ‘bad’=4 and ‘very bad’=5) for the vignette question, the vector X_i is a vector of observed characteristics (the socio demographic covariates across which we are interested to examine systematic reporting bias for example age, gender, education, income, location etc.).

Estimating Equation:
$$H_i^v = X_i\beta + u_i \quad (1)$$

The underlying assumption for this identification is that since the vignette represents a fixed level of latent health, the difference in cut points by covariates can be attributed to the systematic reporting associated with the X_i s viz. age, gender, education level, income quintiles, sector (rural/urban) or location. The idea is to vary the health status exogenously in each of the hypothetical cases, where any difference in rating of these fixed latent health situations can come from the ‘biases’ one has in estimation of health state. Hence in estimation (1) the coefficient β would identify the reporting bias, where a positive (negative) and significant coefficient would imply over-report (under-report) of worse health, as degree of worse health /difficulty increases from 1 to 5 in the categorical response of the dependent variable.

Economic circumstances and geographic location may alter health expectations through factors like peer effects, societal norm and access to medical care hence we include the sector and a dummy for level of development in the state⁶. Reporting of health may vary with education through the awareness factor i.e. conceptions of illness, understanding of disease and knowledge of the availability, access and effectiveness of health care. Etilé and Milcent (2006) provide

⁶ We use the WHS ranking of development in the sample state (based infant mortality rate, female literacy rate, percentage of safe deliveries and per capita income at the state level).

evidence of a convex relationship between reporting heterogeneity and income. Banerjee et al., (2004) finds that individuals in the upper third income group report the most symptoms over the last 30 days, and attribute this to higher awareness of health status. Thus, in order to identify any nonlinear effect of income on reporting bias we include expenditure quintiles constructed from average overall monthly household spending. In order to see whether reporting bias varies by true health we include the measured body mass index categories (viz. underweight, normal, overweight and obese).

Thus, reporting of health status can be influenced by expectations for own health, tolerance of illness, health norm in one's society, which may be in part affected by an individual's socio-economic environment and demographic characteristics. Hence the X vector includes education categories, gender, age groups, body mass index (BMI categories), expenditure quintiles, religion, ethnic groups, sector (urban/rural), underdeveloped state dummy-capturing development in the state (which implicitly captures and controls for the access to effective health care and can be a rough measure for tolerance of illness in the society).

Reporting of health may vary with education through the awareness factor i.e. conceptions of illness, understanding of disease and knowledge of the availability and effectiveness of health care. To test for this we include six education categories capturing the highest level of education completed: no formal education (reference category), less than primary education, primary, secondary, high school and college or above. Age is categorized into four groups: 18 to 29.9 years (reference category), 30 to 44.9 years, 45 to 60 years and greater than 60.

In our second empirical approach we attempt to identify reporting behavior from variation in self-reported health beyond what is explained by 'true' health as approximated by a battery of objective health measures/performance tests, to cross-examine the reporting behavior as indicated by variation in the evaluation of given health states represented by hypothetical case

vignettes. By this exercise we implicitly check whether ‘response consistency’ assumption holds which is necessary for any vignette study to be valid.

We consider a sufficiently comprehensive set of objective indicators of health that include physical measurements, scores from performance tests and interviewer impressions. We specifically examine if for a given level of true health (as approximated by an array of measured tests, clinical diagnosis and measured anthropometrics) there exists reporting bias by the socio-demographic covariates (like education, gender, age, income, sector and location) in a systematic way, and whether this pattern of bias identified for each covariate is same as indicated by the earlier approach.

Let H^{rep} be the response to any self-reported health question (for example ‘how would you rate your health today’) having the following values for the options; ‘very good’=1, ‘good’=2, ‘moderate’=3, ‘bad’=4 and ‘very bad’=5. We regress the self reported health on the same set of covariates (X_i) but now controlling for a battery of ‘objective’ health measures. The underlying idea is any systematic variation in subjective assessments that remains after conditioning on the objective indicators can be attributed to systematic biases in reporting behavior.

$$H_i^{rep} = \alpha H_i^{obj} + X_i b + V_i \quad (2)$$

This specification hinges on the fact that after correcting for ‘true’ health the reporting heterogeneity (if any) would be reflected as the coefficients of the covariates in the second equation. Specifically, the assumption is, adding the precise set of objective indicators in the estimation would soak up the variation coming from the true/latent health, leaving aside the reporting effects to be identified. So a statistically significant negative coefficient for any covariate would mean the higher probability to report better health in that subgroup compared to the reference group.

The next section discusses the data that we use to estimate these two equations, followed by a brief discussion of the summary statistics for the key variables of interest.

2.4 Data and Summary Statistics

The analysis uses the World Health Survey (WHS)-SAGE Wave 1 survey (carried out from 2007 to 2009) in India⁷. The survey implemented a multistage cluster sampling design resulting in nationally representative cohorts. The data collected included self-reported assessments of health linked to anchoring vignettes, which are hypothetical stories that describe the health problems of third parties in several health domains. This data is special in the sense that it has the information of both ‘subjective’ and ‘objective’/ clinical counterpart of identical health questions in addition to the vignettes.

For India the survey covered six states⁸ namely Maharashtra, Karnataka, West Bengal, Rajasthan, Uttar Pradesh and Assam. The states were selected randomly such that one state was selected from each region as well as from each level of development category. The level of development was based on four indicators⁹ namely: infant mortality rate, female literacy rate, percentage of safe deliveries and per capita income at the state level. We use the development

⁷ Implementation of SAGE Wave 1 was from 2007 to 2010 in six countries over different regions of the world (China, Ghana, India, Mexico, Russian Federation and South Africa)

⁸ The 19 states were grouped into six regions: north, central, east, north east, west and south. The sample was stratified by state and locality (urban/rural) resulting in 12 strata and is nationally representative. Of the 28 states, 19 were included in the design which covered 96% of the population.

⁹ A composite index of the level of development was computed by giving equal weightage to the four indicators.

classification¹⁰ used in WHS to construct a dummy for underdevelopment (=1 for the two least developed states, viz. Rajasthan and Uttar Pradesh, and =0 for the other four states).

2.4.1 Information on Vignettes

The following sets of vignettes¹¹ in the data included: Mobility and Affect, Pain and Personal Relationships and Vision, Sleep and Energy, Cognition and Self-care. Each individual questionnaire includes only one set of vignettes and each respondent is asked two questions from each vignette. So, around one-fourth of the total sample responds to vignettes questions on each health domain. In all vignettes the region-specific female/male first names are used to match the sex of the respondent. Before reading out the vignette the interviewer insisted the respondents to think about these people's experiences as if they were their own. The interviews were done face-to-face with the selected respondents in the local language(s).

The respondent was asked to describe how much of a problem or difficulty the person in the vignette has, in an ordered scale response from 1 to 5 - the same way that they described their own health.

2.4.2 Self-reported and Objective measures of health

The survey data includes perceptions of well-being and more objective measures of health, including measured performance tests: rapid walk; cognitive tests (verbal fluency, immediate and delayed recall capacity, digit span forward and backward). In the self-evaluation, interviewees responded to direct questions about their own health state, aimed at capturing their

¹⁰ The states were ranked in this decreasing order of development (Maharashtra> Karnataka> West Bengal> Assam> Rajasthan > Uttar Pradesh) based on the composite index of infant mortality rate, female literacy rate, percentage of safe deliveries and per capita income.

¹¹ A list of the vignette questions are included in the [appendix](#).

perceptions regarding each state of health domain, formulated as, “*Overall, in the last 30 days, how much difficulty did you have in carrying out such activity?*”, the responses of which were obtained on a scale of 1 to 5 (1 = none; 2 = mild; 3 = moderate; 4 = severe; 5 = extreme/cannot do). The key question on self-reported health in the analysis is ‘*How would you rate your health today?*’ The response categories were ordered starting from very good, good, moderate, bad, very bad taking value 1 to 5 respectively. Figure 2.1 shows the distribution of the response categories for self-reported health question. As expected, the percentage of individuals who actually report ‘extreme good’ or ‘extreme bad’ health is very less. However, as it is evident from Figure 2.1, there is enough variation in the SAH to be utilized in regression equation (2) coming from the ‘good’, ‘moderate’, and ‘bad’ categories.

For each adult respondent, the health worker measured height, weight, grip strength, lung capacity, blood pressure, pulse rate and undertook a battery of performance tests for the respondent in various health domains including memory and mobility. We construct four categories of individuals by body mass index by using the measured height and weight: Underweight (BMI < 18.5), (Normal BMI 18.5-24.9- reference category in regression), Overweight (BMI 25-29.9), Obese (BMI >30). Body mass index (BMI) information was included in equation to control for a respondent's risk for different health conditions. The distribution of BMI in the sample is shown in Figure 2.2.

For the domain of mobility we have a set of self-reported variables pertaining to difficulty level in moving around and performance of daily activities in the last 30 days. The distribution of the key question on self-reported mobility in the sample is shown in Figure 2.3.

For objective mobility indicators we have a rapid walk test along with the interviewer’s impression of any walking difficulty of the respondent. In the domain of cognition we have self-reported measures of how the individuals would rate their memory and cognition. The following

tests are taken to measure cognitive ability: immediate and delayed recall (memory); digit span (concentration and memory); verbal fluency¹².

We have some information of semi-objective measures comprised of reported diagnosed chronic disease including arthritis, stroke, angina, diabetes chronic lung disease, asthma, depression, hypertension, cataracts, oral health, injuries, cancer screening, that we include in estimation (2) for robustness checks. We take the total number of reported chronic illness in the estimation. This is implicitly assigning the same weight for all the diseases, and we check also including these as dummies.

The total number of individuals who have the complete information¹³ across measured health are 10873 individuals for which the summary statistics are presented in Table 2.1. The comparison of measured and self-reported height across population subgroups yields very interesting results. Figure 2.4 and Figure 2.5 depicts the graph of average measured and self reported heights across expenditure quintiles and education categories respectively. The education categories capture the highest level of education which is categorized into six groups: No formal education (=1), below primary(=2), primary (=3), secondary(=4), high school(=5), college and above(=6).

From Figure 2.4, we find on average individuals underreport their true height, which is statistically different than measured height across all expenditure quintiles. Quite as per our expectation this difference becomes smaller as we go up the expenditure quintiles and for higher education categories. For individuals with highest education that of college and above, this gap is no longer statistically significant. However, this trend is more or less similar by gender.

¹² Respondent is given one minute to tell the names of as many animals (including birds, insects and fish) that they can think of.

¹³ Around 500 observations do not have scores/not measured on some performance tests, i.e. less than 5% of the sample had missing information on X's, however they were not dropped from the analysis.

Disaggregating by development level of the states (Figure 2.6), we find this difference in reported height and measured height is most prominent across individuals from the poorest quintiles, and the pattern of reporting bias is different for each state. While in relatively more developed states this gap reduces for higher expenditure quintiles (Maharashtra and West Bengal), we do find for less developed states (Rajasthan, Uttar Pradesh, Assam) that this gap persists even for higher expenditure quintiles. By contrast, in the most developed state from our sample, this gap is no longer significant for individuals from second expenditure quintile onwards. Interestingly, while we find individuals on average under-report their true height in Assam, Rajasthan, West Bengal and Maharashtra, there is significant over-report of true height on average in Uttar Pradesh and Karnataka (Figure 2.6).

The picture is very similar across education categories as well (perhaps because of high correlation between education and income), where the difference between average true and reported height is the largest and significant in the lowest education groups across all the states under consideration. We compare the most developed state from our sample, viz. Maharashtra, with a lesser developed state, Rajasthan in this regard (Figure 2.7). Interestingly, we find that the gap between true and self reported height is significant in Maharashtra for only individuals with education level below primary. However, it is not the case in Rajasthan where this difference is significant and persists for individuals even with secondary schooling.

While doing a similar exercise examining the difference between the mean of measured and self-reported weight (Figure 2.8) by expenditure quintiles and level of development we find that the gap between the mean measured and self-reported weight is significant across all expenditure quintiles (except the richest quintile) for less developed states. However this is not so in developed states, where this gap is not statistically significant for any of the expenditure quintiles. The findings seem to suggest that individuals from lesser developed states (correlated

with lesser education and lower access to health facilities) are likely to have different reporting behavior as compared to the ones from developed states. This has important implications given that heterogeneity at the state level do not typically gets controlled in estimations. In the next section we discuss and attempt to connect this suggestive finding of the summary statistics with our regression estimates followed by robustness checks.

2.5 Results

Equation (1) is estimated separately for 10 health state vignettes from each health domains. The regression estimates of the domains ‘Mobility and Affect’ ‘Pain and Personal Relationships’, ‘Vision, Sleep and Energy’, and ‘Cognition and Self-care’ are presented in Table 2.2.1, Table 2.2.2, Table 2.2.3, Table 2.2.4 respectively and the sign and statistical significance of the parameters from these forty separate regressions are summarized in the Table 2.2. All the ten specifications for each health domain include dummies for education categories, gender, age groups, marital status, body mass index categories, household expenditure quintiles, religion, caste, sector and level of development in one’s state.

From the regression estimates of equation (1) we do find a strong evidence of reporting bias across specific population sub-groups for all the health domains. In mobility and affect domain (Table 2.2.1) we find that the ‘male’ dummy is negative and statistically significant for all the vignette questions for mobility¹⁴. This finding reveals that males have a greater probability of underreporting worse health than females in the sphere of mobility. We get an interesting result by the expenditure quintiles. We find that individuals from both lower as well as higher quintile have higher probability to report better health compared to the middle income group. Individuals from urban are more likely to under-report worse health, however the effect is statistically

¹⁴ The dependent variable in specification 1,2,5,6,9 and 10 deals with Mobility, while dependent variable in specification 3,4,7 is on Affect.

significant in half of the regressions. In this domain, individuals who are above 60 years of age have higher probability of reporting ill health, statistically significant in half the cases. The dummy for underdevelopment is negative and statistically significant in almost all of the regressions.

To summarize the regression estimates of the vignette questions across all the health domains we find some interesting results (Table 2.2). Males, on average, show a clear pattern of under-reporting of worse health consistent across all the health domains¹⁵. Out of 40 regression estimates in 72% of the cases, the coefficient on male dummy was found to be negative where it is statistically significant more than half of the time. With regards to the age group, we find with reference to young individuals 18-30 years of age, individuals over 60 years age tend to over-report illness. (The concerned coefficient is positive in 32 cases out of 40 estimations and statistically significant around 50% of the time). This is a pretty standard result in the literature where over-report of worse health is observed for aged individuals. With reference to marital status, we find compared to unmarried/divorced/widowed individual group, currently married individuals tend to under-report illness, although this is not statistically significant most of the time.

Interestingly, those who are underweight and obese mostly tend to over-report worse health compared to individuals with normal body-mass index. With respect to household expenditure quintiles, we find that individuals from the poorest expenditure quintile tends to under-report ill health as compared to individuals from the third quintile, consistently across all the health domains. We do not get any clear pattern of reporting bias across religion or caste groups, although we see some pattern by specific health domains. For instance, in the domain of

¹⁵ The only exception being in the health domain of pain and discomfort, where male dummy changes sign and is actually positive and significant in 3 estimations (Table 2B).

mobility- while hindus were found to underreport ill-health, scheduled castes were more likely to over-report ill-health. The urban dummy is consistently negative across all the domains suggesting urban individuals tend to under report ill health as compared to rural, and the effect is statistically significant for 57% of the total cases.

Perhaps the most interesting result out of this exercise is the evidence obtained for systematic reporting bias by different states in India. In comparison to the developed states, the underdeveloped state dummy is negative 88% of the cases, and statistically significant around 80% of the time. Quite strikingly, for the health domains of vision, sleep and energy (Table 2.2.3), ‘cognition and self-care’ (Table 2.2.4) we find the underdeveloped dummy is negative and statistically significant for *all* the estimates without any exception.

Hence, if we think that this current definition of underdevelopment captures the health access and health standards in the community, we find a stark difference in reporting pattern from the social disadvantaged states. This is perhaps suggestive of the hypothesis that socially disadvantaged individuals fail to perceive and report the presence of illness or health-deficits because an individual’s assessment of their health is directly contingent on their social experience. It can perhaps be attributed to lower expectation for own health/higher tolerance for diseases where a particular individual may not see herself as being unhealthy conditional on the health norm/standard prevailing in one’s community.

We now discuss the findings from the cross-validation exercise estimating equation (2) and comment on the validity of ‘response consistency’ assumption across different health domains. We first estimate the dependent variable ‘*how would you rate your health today*’ on the same set of covariates as used in earlier estimation of equation(1), but now including a set of performance tests and interviewer assessments across different health domains in Table 2.3. We gradually add objective health information in our specification from (1) through (4) and examine

if the addition of more objective information on several health domains completely absorb the variation coming from variation in latent health, leaving only effects that identifies reporting bias.

Specification (1) includes dummies for highest education level, gender, age groups, marital status, expenditure quintiles, religion, caste, sector and level of development in the state. Specification (2) also controls for body mass index categories in addition to controls included in specification (1). We further add (i) the performance test scores for mobility and cognitive ability (ii) biomarkers including tests for lung function; blood pressure (systolic and diastolic); pulse rate; total number of chronic illness diagnosed from (arthritis, stroke, angina, diabetes chronic lung disease, asthma, depression, hypertension, cataracts, oral health, injuries, cancer screening) in specification (3) on top of the controls in specification (2). The last specification (4) adds interviewer assessment dummies for whether the respondent had any problem in the following domain: hearing, vision, walking, shortness of breath, and whether she/he had any overall health problem.

We find individuals with education level secondary and above are more likely to under-report illness that is statistically significant at 1% level across all specifications. The result can perhaps be explained if highly educated respondents feel greater confidence regarding their capacity to handle a given level of health impairment, and thus under rate it more, after controlling for other factors.

Males show consistent patterns of under reporting illness as compared to females, which is again statistically significant for all the specifications. We find compared to the young age group of 18-30 years, with higher age- particularly individuals over 60 years- significantly over report illness, which is consistent with our earlier finding from vignette approach.

We do not find significant difference in reporting bias by marital status. Once we control for objective health information the coefficients lose statistical significance in specification (3)

and (4). With respect to household expenditure quintiles we find compared to the middle expenditure group both the poor and the rich tend to understate illness, however this effect is statistically significant only for the highest expenditure group. We also do find statistically significant under-reporting of worse health among urban cohort, hindu and scheduled castes.

To confirm our earlier findings about reporting bias by development level in the state- we find a very strong evidence from this estimation exercise- the underdeveloped dummy is found to be consistently negative and statistically significant across *all* the specifications, implying a underreporting of worse health among the disadvantaged group. Once we control for the interviewer assessments of health states in specification (4) the magnitude of the coefficient on the underdeveloped dummy even rises, confirming that it is picking up reporting bias.

Interestingly across the body-mass index categories we do find statistically significant evidence of over-reporting of worse health among the underweight population, as indicated by our earlier findings. The objective health indicators of rapid walking ability, cognitive score, chronic illness, and interviewer assessments of health situation were all found to be significant and with expected signs, which is reassuring as it implies that better objective/measured health leads to more probability of reporting better health.

We further estimate a vector of self reported functioning measures in the domain of mobility (results shown in Table 2.4) and daily activities (in Table 2.5). In the estimation for self-reported mobility we include walking speed, which is predictive of overall health and mobility, level of disability. Specifications (1) through (12) control for some objective health measures that are likely to approximate mobility level (performance tests for timed and rapid walk, interviewer assessment for difficulty in mobility and dummies for body mass index categories) along with the usual covariates: highest education level, gender, age groups, marital status, expenditure quintiles, religion, caste, sector and level of development in the state.

The dependent variables in all the specifications in both Table 2.4 and Table 2.5 takes value 1-5 measuring self reported difficulty level (1=no difficulty; 5=extreme difficulty) faced by the respondent in the specific activity describing some form of mobility (for example in moving around, walking, picking up, crouching, vigorous activities etc.) and daily activity(for example performing household activities, getting to places, washing body, using toilet, carrying etc.). The summary of signs and statistical significance of the estimated coefficients from both these set of regressions from Table 2.4 and Table 2.5 are summarized in Table 2.6. The findings reveal systematic underreporting of worse health among higher educated group, urban and underdeveloped states, again reconfirming our earlier findings.

In the similar spirit we regress self-reported cognitive outcomes (for example how much difficulty one had in remembering and concentrating thing) including objective measures (test of words recalled after delay, digital recall test and verbal fluency) on the same set of covariates as before. The findings (Table 2.7) reveal again the same pattern of reporting bias as identified earlier in vignettes study and resemble the findings from equation (2) in the domains of mobility and general health.

As a further robustness check we regress the objective scores of memory on these covariates (Table 2.8) and check whether males, underdeveloped actually fare better on this. Now this would be a weak test for accepting reporting bias if the covariates which are likely to underreport worse health were also likely to have better objective health; however, one can assume that this serves as a strong test to identify reporting bias in case the direction of bias/sign of coefficients obtained from self-reported response are found to be opposite in comparison to that obtained in estimation of objective health. Interestingly for the dependent variable 'words recalled' we find quite the opposite result for male dummy compared to what was suggested by self-reported memory. While estimation of self-report measure for memory would suggest that

males fare better, we find contrary result when we estimate objective memory test for words recalled. This robustness check provides support that males do in fact understate worse health. Similarly, while self-reported memory measure suggested that individuals from underdeveloped states are better off, in contrast when we estimate the objective measures on the same set of covariates we get individuals from underdeveloped states fare worse in this regard, which is statistically significant, confirming our previous findings. As expected individuals from underdeveloped states were found to score lower on both cognitive tests as indicated by the negative and statistically significant coefficient in specification in (2) and (3) in Table 2.8.

In the similar spirit as a further robustness check we estimate objective measures of mobility and general health in Table 2.9 using interviewer assessments on the same set of covariates (specification 1 and 3), and also controlling also for body mass index categories (specification 2 and 4). We find that after controlling for body mass index categories males in fact fare worse in assessed walking difficulty, which falls in line to what was suggested by our earlier results about systematic under-reporting of worse health in self reported health. Interestingly, coefficient on the underdeveloped dummy for interviewer assessed health problem reveals that individuals from underdeveloped states were more likely to have health problems, which is statistically significant for both specification (2) and (3). This reconfirms our earlier findings and supports the prevailing view of perception bias.

We further utilize individual fixed effects¹⁶ to figure out how much of the variation in individual reporting heterogeneity still remains even after inclusion of the covariates in the estimation of vignette response. The idea behind this exercise is that even though systematic reporting heterogeneity by observables can be accounted for controlling for the covariates in the regression, it remains to be seen how much of the variation remains even after accounting these,

¹⁶ Each individual answers 10 vignette questions in a set

i.e., what remains to unexplained due to unobservables . This exposes the gravity of the underlying problem that non-random measurement error can be accounted as far as the observables allow, and also helps to check the robustness of the previous findings.

We carry this exercise using two-stage regression estimation. In the first stage we regress the vignette responses (10 questions per vignette set for each individual) on individual dummies ID_i to get their corresponding coefficients μ 's which we use in the second stage as dependent variables to be explained by the usual covariates. Precisely we examine to see how much of individual reporting bias can be explained by including the observables and what part remains to unexplained even after accounting for the usual covariates. We estimate the following set of equations:

$$H_i^v = ID_i \mu + v_i \quad (3)$$

$$\mu = X_i \beta + u_i \quad (4)$$

We present the results in table 2.10. We present the histogram of the estimated coefficients in Figure 2.9, Figure 2.10, Figure 2.11, Figure 2.12. The distribution reveals substantial reporting heterogeneity across individuals (significantly different from zero), for which we examine how much of this can be explained by the covariates. The OLS regression estimates are presented in Table 2.10. The results confirm our previous findings. Precisely we get males were more likely to favorably rank their health state (statistically significant for vignette set A and C); individuals above 60 years were likely to overstate bad health (statistically significant for vignette set A, C and D). Both the quintiles above and below the middle expenditure group were likely to understate ill health. Again we get striking result for the level of development in the state, where the underdeveloped dummy is always significant and negative for all the four sets of vignettes.

This has important implications given the fact that heterogeneity within country, at the state level is often not included as control, and as we find we have substantial systematic heterogeneity along this line, that can mess up the statistical inference. However it is reassuring to find that the pattern of systematic bias indicated by the vignettes exercise through equation (1) seems to be in line with the results obtained from the two-stage estimation, and hence this lends support to the use of vignettes in identifying this bias.

Also, important to note here is that the R-square for estimations (1) to (4) is just explaining 3% (in domain of Mobility and affect) to 7% (in domain of Cognition and self care) of the variation in the self reported behavior. This is alarming given that we get to only control for the observables in the regression, which even after adjusted for leaves much reporting heterogeneity at the individual level typically unaccounted for. We did try to check including the interaction terms of the covariates without much improvement in the R square. Hence this reinstates the point that biases in self-reported measure cannot even be fully controlled by identifying and accounting for the sources of systematic measurement error across the observables.

2.6 Conclusion and Policy insights

One of the key challenges in the analysis and interpretation of health survey data is improving the interpersonal comparability of subjective indicators- that comes with systematic measurement error- as a consequence of differences in the ways that individuals understand and use the available responses for a given question. In this paper we examine the pattern of reporting differences in SAH from a nationally representative survey in India and find evidence that measurement error in SAH systematically varies with demographic characteristics, such as the

age, gender, education and community characteristics such as sector and level of development in the state. This has important implications on several aspects.

First one should be careful in inter-personal comparison of health status using self-reported health data. This will be particularly important with regard to measuring performance in achievement of the government targets in improving population health, for instance one of the Millennium Development Goals has been targeting to reduce child and maternal morbidity, where reporting of diagnosed illness is the primary source for identifying the incidence of a disease, collected through household surveys (Dixon et al. 2007).

With the increased interest in health issues in children, women of reproductive age and elderly, self-reported data on morbidity, utilization and expenditure on health care, perceived well being¹⁷, self-rated ranking of health service delivery used in citizen and community report cards needs to be carefully used in inter-personal comparison. Government reports based on self-reported indicators collected on maternity care and immunization for a comparison of health expenditure profile across households or in drawing causal inference of a program needs to be re-examined in the light of this problem. Further one has to reflect on the problem that non-random measurement error cannot be simply dealt with by controlling for the covariates in a typical regression framework.

The findings provide a strong empirical evidence to confirm the prevailing view that socially disadvantaged individuals (as captured here by residing in a less developed state) fail to perceive and report the presence of illness or health-deficits. Hence, even within a country there is strong evidence on systematic reporting bias, hence the problem of cross-population comparability with self-reported data remains a serious issue. This also calls for paying special attention to account for state-level heterogeneities in typical regression estimations to reduce

¹⁷ Gilligan & Hoddinott 2009 use self-perceived well being as an outcome of interest in examining the causal impact of PSNP-food security program in Ethiopia.

some of the issues with systematic bias by the socio-economic disadvantage level of the community.

The findings presented here suggest that it is necessary to account for how different population subgroups/individuals see and evaluate their health using different thresholds and thus it calls for adjustment for systematic variation in measurements of self-rated health. The current evidence indicates that self-reported measures of health cannot be directly compared across population sub-groups, because groups differ in how they use subjective response categories. The problem is further complicated as this systematic variation cannot be accounted for by just including the socio-economic characteristics in a typical regression framework. The challenge is to develop alternative strategies to reduce the subjective variation in health perception in its various domains and to make possible greater comparability between distinct socio-economic groups.

This analysis lends support to the use of vignettes data to use them to identify the bias in SAH data in a developing country setting and obtain bounds on the bias as well. One of the policy insights that comes out of this analysis is that it would be prudent to enrich the individual and household surveys by adding questionnaire with a section on the vignettes that would help identify the thresholds one is using for SAH thus making it feasible to be used for statistical inference.

For future work we plan use the external vignette information to separately identify the thresholds and cut-offs of any systematic reporting heterogeneity, which can be imposed on the model for the self-reports with respect to the individual's own health, so that estimates would reflect true health differences rather than a mixture of health differences and reporting heterogeneity. We also plan to examine the extent of bias induced by using self-reported health as opposed to objective measures in estimation of wage/ employment in human capital model,

taking data from this survey. Additionally we plan to examine more clear patterns of reporting bias by incorporating the interaction of the covariates as controls to help identify the finer sources of variation.

References

- Antman, Francisca, and David McKenzie. (2007) Earnings Mobility and Measurement Error: A Pseudo-Panel Approach, *Economic Development and Cultural Change* 56(1):125.
- Baron-Epel, O., Dushenat, M., & Friedman, N. (2001) Evaluation of the consumer model: relationship between patients' expectations, perceptions and satisfaction with care, *International Journal for Quality in Health Care*, 13(4), 317-323.
- Bago d'Uva, T., Doorslaer, E.V., Lindeboom, M., O'Donnell, O.,(2008) Does reporting heterogeneity bias the measurement of health disparities? *Health Economics* 17,351–375.
- Bago d'Uva, T., Lindeboom, M., O'Donnell, O., Van Doorslaer, E. (2010) Slipping anchor? Testing the vignettes approach to identification and correction of reporting heterogeneity. mimeo. Erasmus School of Economics.
- Banerjee, A., Deaton, A., & Duflo, E. (2004) Health, health care, and economic development: Wealth, health, and health services in rural Rajasthan., *American Economic Review*, 94(2), 326.
- Bound John(1991) Self Reported Versus Objective Measures of Health in Retirement Models,*Journal of Human Resources*.;26(1):107–137.
- Currie, J., Madrian, B.C. (1999) Health, health insurance and the labour market, *Handbook of Labour Economics*, Vol. 3, Ashenfelter, O., Card D. (eds.). Elsevier: Amsterdam.
- Datta Gupta, Nicolai Kristensen and Dario Pozzoli (2010) External validation of the use of vignettes in cross-country health studies, *Economic Modeling* 27 (2010) 854–865.
- Dixon-Mueller, R., & Germain, A. (2007). Fertility regulation and reproductive health in the Millennium Development Goals: the search for a perfect indicator. *Journal Information*, 97(1).
- Escobal, J., & Laszlo, S. (2008) Measurement Error in Access to Markets, *Oxford bulletin of economics and statistics*, 70(2), 209-243.
- Etile, F and Carine Milcent (2006) Income-related reporting heterogeneity in self assessed health: evidence from France, *Health Economics*, Vol. 15, pp 965-981.
- Gerdtham, U-G., Johannesson, M. (2001) The relationship between happiness, health, and socio-economic factors: Results based on Swedish micro data, *Journal of Socio-Economics* 30, 553-557.
- Grol-Prokopczyk, H., Freese, J., & Hauser, R. M. (2011) Using anchoring vignettes to assess group differences in general self-rated health, *Journal of health and social behavior*, 52(2), 246-261.
- Gwatkin (2000)Health inequalities and the health of the poor: What do we know? What can we do? *Bulletin of the World Health Organization*, vol.78.

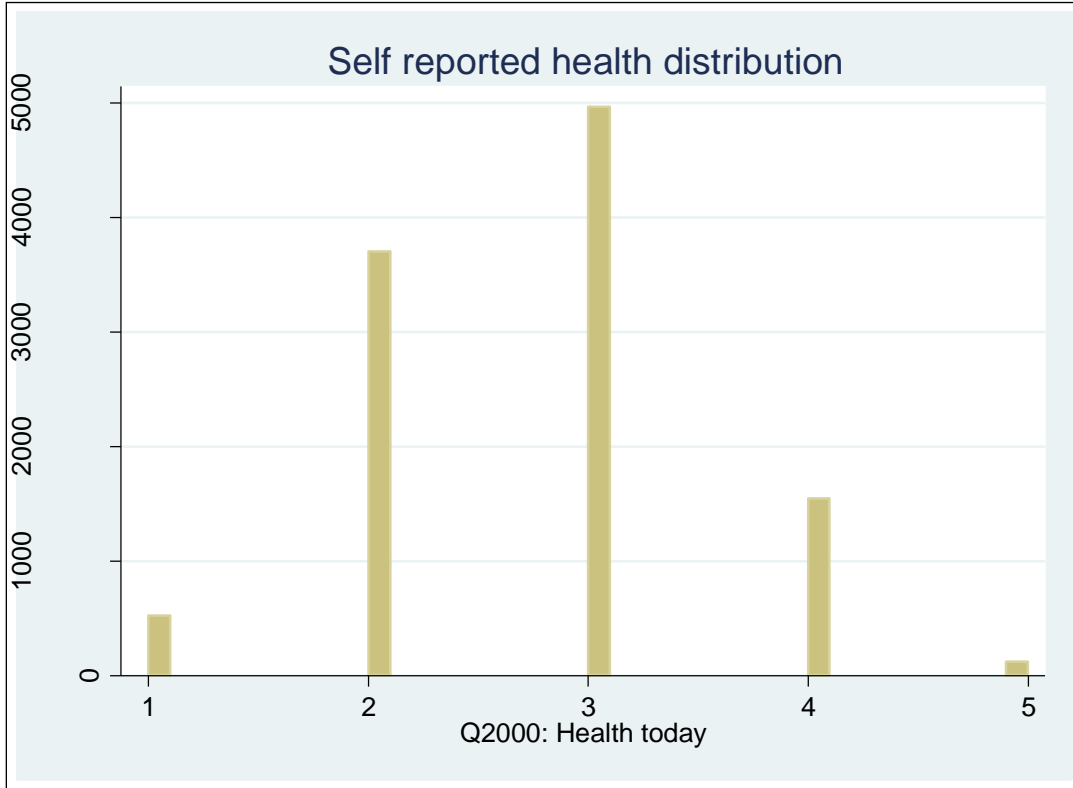
- Jones, A and Angel Nicholas (2002) The importance of individual heterogeneity in the decomposition of measures of socioeconomic inequality in health : an approach based on quantile regression, Ecuity II Project.
- Johnston, D. W., Propper, C., & Shields, M. A. (2009). Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient, *Journal of health economics*, 28(3), 540-552.
- Jürges, H. (2007) True Health vs Response Styles: Exploring Cross-Country Differences in Self-Reported Health, *Health Economics*, 16(2), 163-178.
- Kakwani N, Wagstaff, A., and E. van Doorslaer (1997)Socioeconomic inequalities in health: Measurement, computation, and statistical inference, *Journal of Econometrics* 77,pp 87-103.
- Kapteyn, A., Smith, J.P., van Soest, A., (2007) Vignettes and self-reports of work disability in the United States and the Netherlands, *American Economic Review* 97 (1), 461–473.
- Kerkhofs, M.K.M., Lindeboom, M., (1995) Subjective health measurements and state dependent reporting errors, *Health Economics* 4, 221–235
- King, G.A., Murray, C.J.L., Salomon, J.A., Tandon, A., (2004) Enhancing the validity and cross-cultural comparability of measurement in survey research, *American Political Science Review* 98 (1), 191–207.
- Krause, N. M., & Jay, G. M. (1994) What do global self-rated health items measure? *Medical care*, 930-942.
- Lindeboom, M. and E. van Doorslaer (2004) Cut-point shift and index shift in self reported health, *Journal of Health Economics* 23 (6), 1083–1099.
- Mishra, S. (2004). Public health scenario in India. *India development report*, 5, 62-83.
- Murray, C.J.L., A. Tandon, J. Salomon, C.D. Mathers, and R. Sadana (2001) “Cross-Population Comparability of Evidence for Health Policy,” Global Programme on Evidence for Health Policy Discussion Paper, Geneva: World Health Organization.
- Rohrer, J. E. (2009). Use of published self-rated health-impact studies in community health needs assessment, *Journal of Public Health Management and Practice*, 15(4), 363-366.
- Schultz, T. P., and A. Tansel, (1997) “Wage and labor supply effects of illness in Cote d Ivoire and Ghana:instrumental variable estimates for days disabled”, *Journal of Development Economics*, 53 (2): 251-286.
- Schultz, T. (2005) Productive benefits of health: Evidence from low-income countries.
- Schultz, T. P., & Strauss, J. (Eds.). (2008) *Handbook of development economics* (Vol. 4). North Holland.

- Sen, A.(1993) Positional objectivity, *Philosophy & public affairs* 22.2: 126-145.
- Sen, A. (2002) Health: Perception versus observation: Self reported morbidity has severe limitations and can be extremely misleading,*BMJ: British Medical Journal*, 324(7342), 860.
- Strauss, J., & Thomas, D. (2007) Health over the life course, *Handbook of development economics*, 4, 3375-3474.
- Strauss, J. and D. Thomas (1996) Measurement and mismeasurement of social indicators, *American Economic Review*, 86.2:30-34.
- Strauss, J., & Thomas, D. (1998) Health, nutrition, and economic development,*Journal of economic literature*, 36(2), 766-817.
- Thomas, D. and J. Strauss (1997) Health, wealth and wages of men and women in urban Brazil, *Journal of Econometrics* , 77: 159-185.
- Thomas, Duncan, and Elizabeth Frankenberg (2002) The measurement and interpretation of health in social surveys, *Measurement of the global burden of disease*: 387-420.
- Van Doorslaer, E and A. M. Jones (2002) Inequalities in self-reported health ; validation of a new approach to measurement, *Journal of Health Economics* ,pp 61-87.
- van Soest Arthur, Delaney Liam, Harmon Colm, Kapteyn Arie, Smith James. (2011) Validating the use of anchoring vignettes for the correction of response scale differences in subjective questions, *Journal of the Royal Statistical Society Series. 3. A* 174; pp. 575–595.
- Wagstaff, A., Eddy van Doorslaer and Naoko Watanabe (2003) On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam, *Journal of Econometrics* 77,pp 207-223.

Table 2.1: Descriptive Statistics

Variables	Mean	Std. Dev.
<i>Education Categories</i>		
No Formal Education	0.45	0.50
Below Primary	0.10	0.31
Primary	0.16	0.36
Secondary	0.12	0.33
High School	0.11	0.31
College and Above	0.06	0.24
<i>Individual Characteristics</i>		
Male	0.39	0.49
<i>Age groups</i>		
18-29.9	0.14	0.34
30-44.9	0.22	0.41
45-60	0.32	0.47
Above 60	0.32	0.47
<i>Marital Status</i>		
Currently Married	0.78	0.42
<i>BMI Categories (measured)</i>		
Underweight (BMI< 18.5)	0.35	0.48
Normal (BMI 18.5-24.9)	0.51	0.50
Overweight (BMI 25-29.9)	0.11	0.31
Obese (BMI>30)	0.03	0.17
<i>Household Characteristics</i>		
Household's Expenditure Quintiles		
Q1	0.21	0.41
Q2	0.16	0.37
Q3	0.22	0.42
Q4	0.22	0.41
Q5	0.17	0.38
Religion (Hindu=1)	0.84	0.37
Caste (SC/ST=1)	0.41	0.49
<i>Regional characteristics</i>		
Urban	0.25	0.43
Underdeveloped dummy (=1 for states: Rajasthan, UP)	0.38	0.49
N=10873		

Figure 2.1: Distribution of Self-reported health response



Note :SAH is on a 1-5 scale , where 1=very good; 5=very poor

Figure 2.2: Distribution of Body Mass Index (BMI) in sample

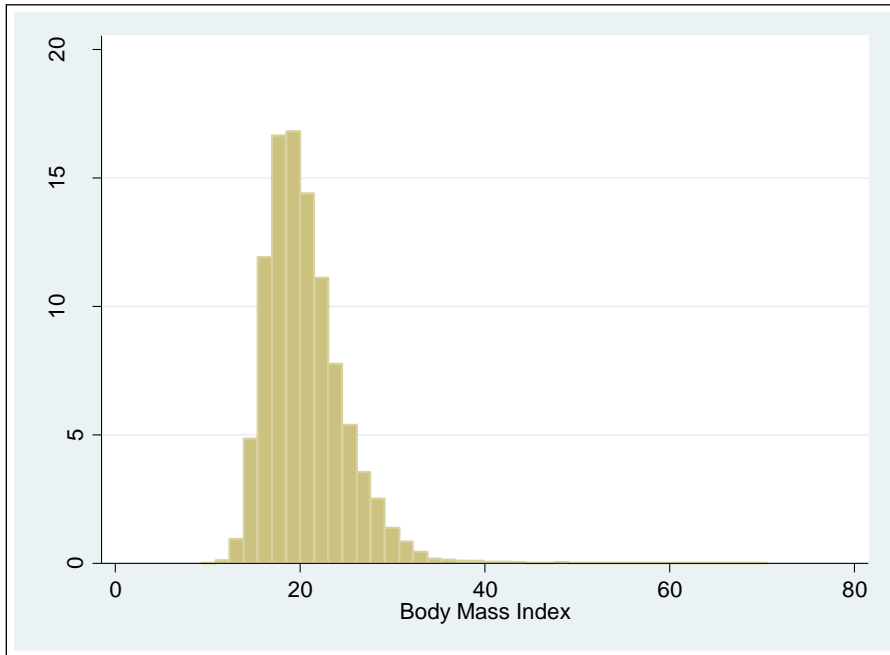
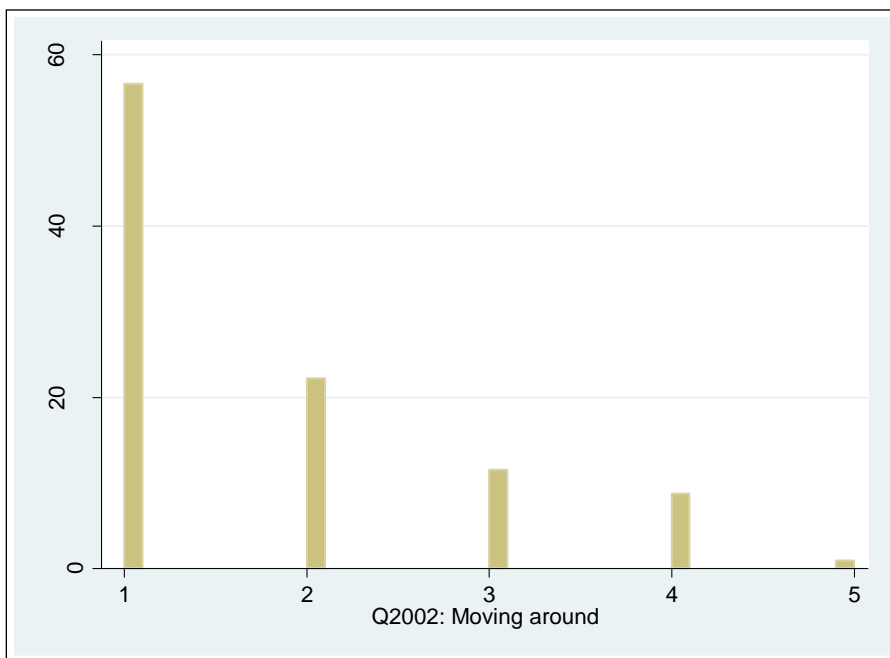


Figure 2.3: Distribution of Self reported mobility



Note :SAH is on a 1-5 scale , where 1=very good; 5=very poor

Figure 2.4: Average self reported and measured height by expenditure quintiles

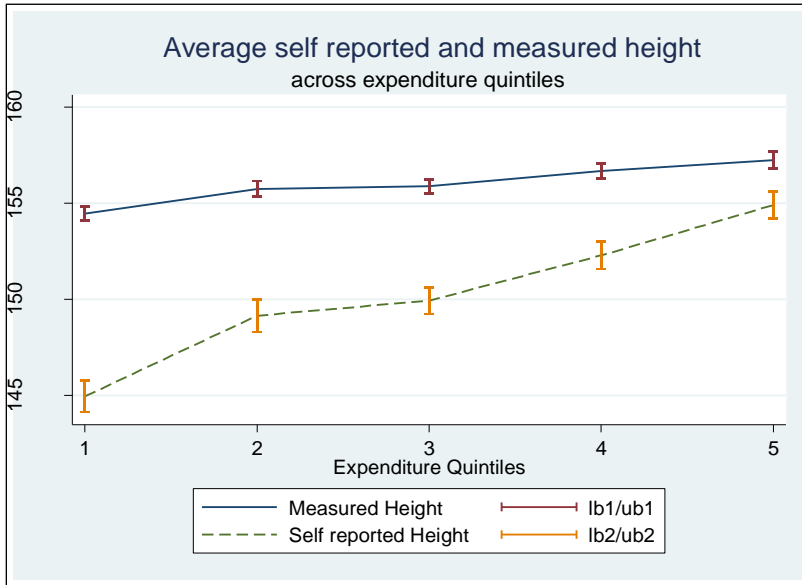
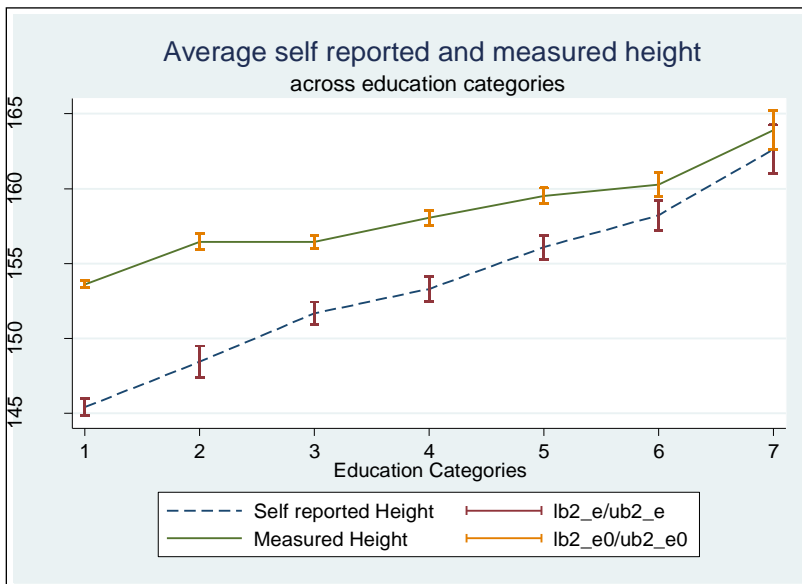


Figure 2.5: Average self reported and measured height by education categories



Note: Categories include: No formal education (=1), below primary(=2), primary (=3), secondary(=4), high school(=5), college (=6) Post-graduate degree completed(=7)

Figure 2.6. Average Self reported and Measured height by expenditure quintiles and state

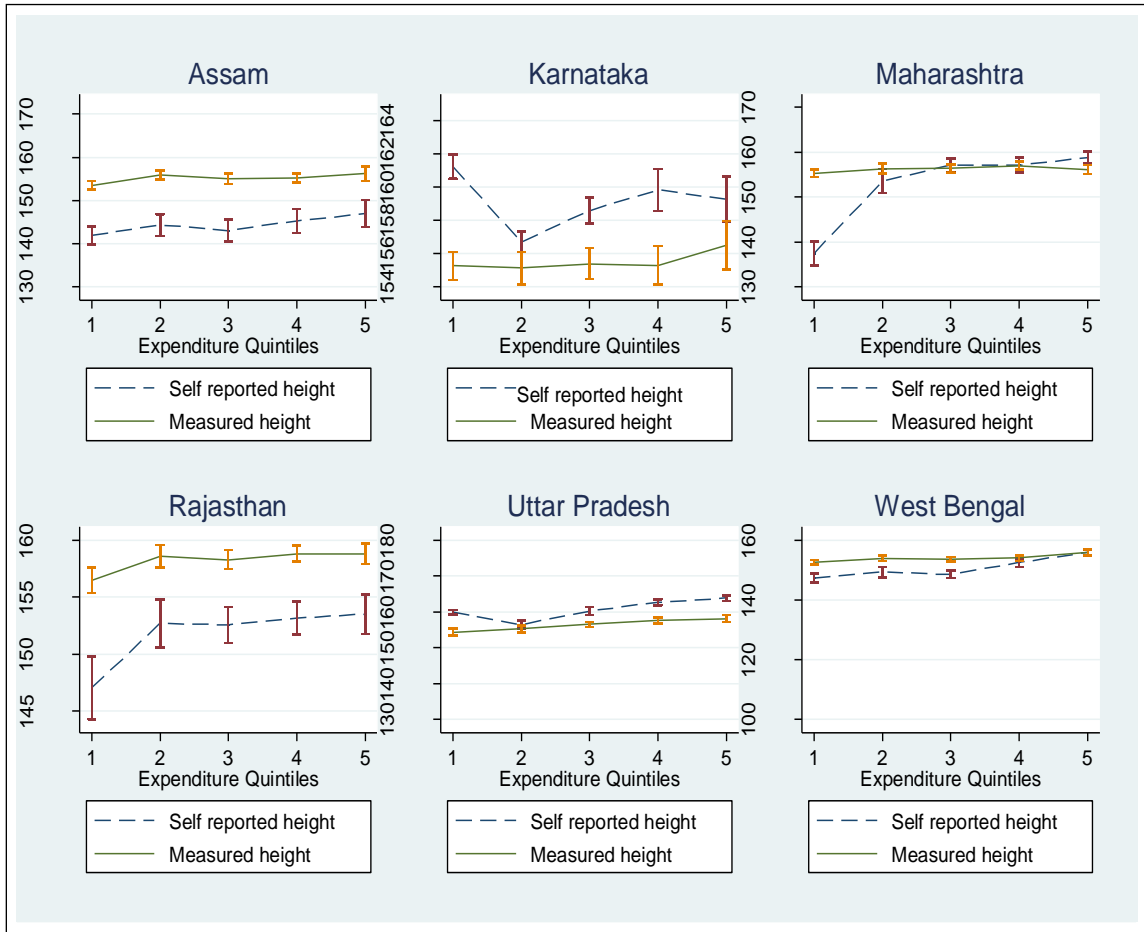
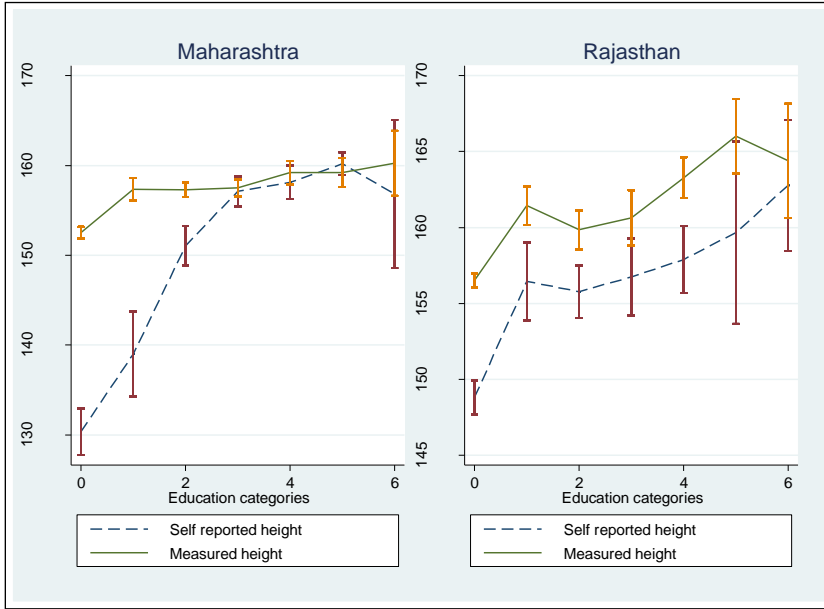


Figure 2.7: Comparison of Self reported and Measured height by education categories in two states.



Note: Categories include: No formal education (=1), below primary(=2), primary (=3), secondary(=4), high school(=5), college and above (=6)

Figure 2.8: Comparison of Self reported and Measured weight by development level and expenditure

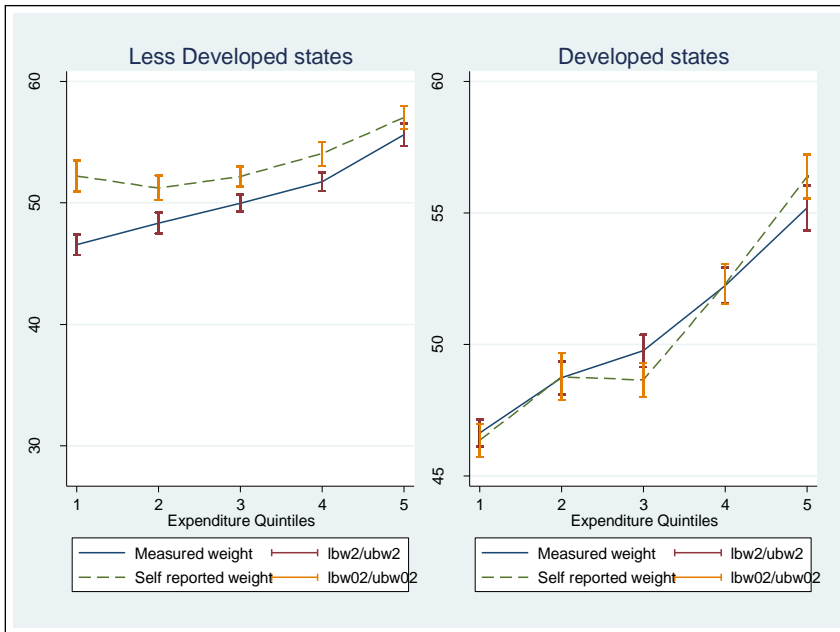


Table 2.2: Summary Table of 40 Ordered Probit Regressions with Vignettes data

Variables	Positive and Significant	Positive and Insignificant	Negative and Significant	Negative and Insignificant
<i>Education Categories</i>				
(Ref category: No formal education)				
Below Primary	2	22	3	13
Primary	0	17	8	15
Secondary	3	13	4	20
High School	5	14	3	18
College and Above	7	15	3	15
<i>Individual Characteristics</i>				
Male	4	7	19	10
<i>Age groups</i>				
(Ref category: Age 18-29.9 years)				
30-44.9	3	27	2	8
45-60	5	20	3	12
Above 60	13	19	1	7
<i>Marital Status</i>				
Currently Married	2	13	6	19
<i>BMI Categories (measured)</i>				
(Ref category: Normal BMI 18.5-24.9)				
Underweight (BMI< 18.5)	5	24	0	11
Overweight (BMI 25-29.9)	2	14	2	22
Obese (BMI>30)	3	19	3	15
<i>Household's Expenditure Quintiles</i>				
(Ref category: Q3)				
Q1	0	8	12	20
Q2	1	17	4	18
Q4	1	16	7	16
Q5	4	18	3	15
Religion (Hindu=1)	1	14	5	20
Caste (SC/ST=1)	16	8	8	8
<i>Regional characteristics</i>				
Urban	0	6	11	23
Underdeveloped	1	4	32	3

Table 2.2.1: Vignettes set 1: Mobility and Affect

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Education Categories</i> (Ref category: No formal education)										
Below Primary	0.02	-0.03	0.19**	0.12	0.01	-0.06	0.07	0.01	0.01	-0.04
Primary	-0.01	-0.07	0.10	0.01	0.04	0.01	0.09	0.03	0.00	0.00
Secondary	0.08	-0.07	0.09	-0.05	0.00	-0.01	-0.09	-0.12*	0.14*	0.03
High School	0.06	-0.09	0.11	-0.01	0.14*	-0.00	-0.09	-0.18**	0.09	0.06
College and Above	-0.07	-0.21**	0.09	-0.07	0.18	0.15	-0.03	-0.10	0.02	0.03
<i>Individual Characteristics</i>										
Male	-0.12**	0.12**	-0.18***	-0.18***	-0.25***	-0.10*	-0.03	-0.10**	-0.15***	-0.05
<i>Age groups</i> (Ref category: Age 18-29.9 years)										
30-44.9	-0.02	0.09	0.03	0.01	0.03	0.02	0.12	0.04	0.17**	0.15**
45-60	0.04	0.09	0.05	0.03	-0.03	-0.03	-0.01	-0.09	0.12*	0.20***
Above 60	0.15**	0.21***	0.13*	0.11	0.12	0.11	0.08	0.03	0.23***	0.26***
<i>Marital Status</i>										
Currently Married	0.06	-0.03	0.01	0.05	0.00	-0.02	-0.02	0.01	-0.06	-0.07
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)										
Underweight (BMI<18.5)	0.01	0.04	-0.07	-0.06	-0.05	0.02	0.03	0.00	-0.06	-0.03
Overweight (BMI 25-29.9)	0.03	-0.01	-0.06	-0.05	0.13*	0.08	-0.20***	-0.15**	-0.02	0.06
Obese (BMI>30)	-0.00	0.23*	-0.15	-0.25*	0.11	0.21	0.01	0.03	0.24*	0.10
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)										
Q1	-0.08	-0.16**	-0.21***	-0.22***	-0.07	-0.18***	-0.10*	-0.13**	-0.17***	-0.14**
Q2	-0.06	-0.06	-0.14**	-0.14**	0.05	0.02	-0.03	-0.06	-0.09	-0.07
Q4	-0.04	-0.06	-0.13**	-0.12**	-0.04	-0.09	-0.04	-0.12*	-0.12**	-0.17***
Q5	0.00	0.06	-0.14*	-0.10	-0.01	-0.02	0.03	-0.02	-0.06	-0.05
Religion (Hindu=1)	-0.06	-0.10*	0.01	0.08	-0.15***	-0.12**	-0.06	-0.05	0.01	-0.07
Caste (SC/ST=1)	0.12***	0.05	0.03	0.03	0.10**	0.10**	-0.03	0.02	0.22***	0.16***
<i>Regional characteristics</i>										
Urban	-0.12**	-0.12**	-0.05	-0.02	-0.04	-0.09*	-0.04	-0.01	-0.09*	-0.14***
Underdeveloped	-0.14***	0.12***	-0.26***	-0.12**	-0.36***	-0.13***	-0.02	0.02	-0.20***	0.05
Observations	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674	2,674

*** p<0.01, ** p<0.05, * p<0.1

Table 2.2.2: Vignettes set 2: Pain and Personal Relationships

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Education Categories</i> (Ref category: No formal education)										
Below Primary	-0.05	-0.09	0.03	0.15**	0.07	0.05	-0.12	-0.05	-0.08	-0.09
Primary	-0.17***	-0.12**	-0.03	-0.02	0.04	0.03	-0.04	-0.01	-0.10	-0.09
Secondary	-0.02	-0.21***	0.09	0.20***	-0.07	-0.02	-0.02	-0.01	-0.01	0.00
High School	-0.01	-0.11	0.03	0.07	0.07	0.03	-0.08	-0.10	-0.01	-0.01
College and Above	-0.19*	-0.25**	0.16	0.23**	0.07	-0.01	-0.13	-0.07	-0.00	0.00
<i>Individual Characteristics</i>										
Male	-0.06	-0.03	-0.08	-0.13***	-0.11**	-0.14***	0.15***	0.13***	0.09*	-0.03
<i>Age groups</i> (Ref category: Age 18-29.9 years)										
30-44.9	0.05	-0.03	0.06	0.11	0.01	0.09	0.02	-0.06	0.01	0.05
45-60	0.02	-0.03	-0.01	0.07	-0.12*	-0.01	0.02	-0.08	-0.03	0.07
Above 60	0.10	0.03	-0.05	0.02	-0.12	0.00	-0.03	-0.09	-0.08	0.05
<i>Marital Status</i>										
Currently Married	-0.05	0.04	-0.11**	-0.09*	-0.08	-0.04	-0.14***	-0.10*	-0.07	-0.02
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)										
Underweight (BMI<18.5)	0.01	-0.02	0.05	0.04	0.02	0.02	0.04	0.04	0.03	-0.01
Overweight (BMI 25-29.9)	-0.02	-0.08	-0.03	-0.02	-0.02	0.04	0.10	0.10	-0.03	-0.01
Obese (BMI>30)	0.10	-0.14	0.05	0.09	0.04	0.01	-0.19	-0.08	-0.21*	-0.18
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)										
Q1	-0.09	-0.11*	-0.15**	-0.05	-0.09	-0.03	-0.11*	-0.08	-0.03	-0.07
Q2	0.07	0.05	-0.08	-0.05	-0.12*	-0.08	0.05	0.09	0.06	0.12*
Q4	0.04	0.09	-0.04	-0.10	-0.08	-0.00	0.04	0.04	0.04	0.02
Q5	-0.05	0.00	-0.13*	-0.16**	0.07	-0.06	0.06	0.08	0.02	0.05
Religion (Hindu=1)	-0.02	0.13**	-0.08	0.00	0.07	0.01	-0.08	-0.06	-0.12**	-0.13**
Caste (SC/ST=1)	0.13***	0.08*	-0.04	-0.09**	0.15***	0.06	-0.12***	-0.11**	-0.06	-0.06
<i>Regional characteristics</i>										
Urban	-0.06	-0.07	-0.01	-0.02	-0.08	-0.00	0.01	-0.03	0.01	-0.03
Underdeveloped	-0.05	0.03	-0.20***	0.01	-0.25***	-0.15***	-0.37***	-0.19***	-0.23***	-0.02
Observations	2,729	2,729	2,729	2,729	2,729	2,729	2,729	2,729	2,729	2,729

*** p<0.01, ** p<0.05, * p<0.1

Table 2.2.3: Vignettes set 3: Vision, Sleep and Energy

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Education Categories</i> (Ref category: No formal education)										
Below Primary	0.12	0.11	0.01	-0.01	0.06	0.09	0.06	0.06	0.03	0.01
Primary	0.01	-0.13**	-0.03	0.03	0.01	-0.11*	-0.08	-0.08	-0.00	-0.08
Secondary	0.08	0.00	-0.04	-0.09	0.18**	0.09	0.07	0.08	0.01	0.00
High School	0.30***	0.14*	-0.06	-0.16**	0.12	-0.00	-0.11	-0.08	0.03	-0.15*
College and Above	0.47***	0.26***	0.05	-0.14	0.17*	0.03	0.24**	0.15	0.18*	-0.03
<i>Individual Characteristics</i>										
Male	-0.07	-0.04	-0.05	-0.08	0.01	0.01	-0.18***	-0.21***	-0.13***	-0.09*
<i>Age groups</i> (Ref category: Age 18-29.9 years)										
30-44.9	-0.04	0.00	-0.03	-0.11	0.15**	0.07	0.05	0.02	-0.02	-0.07
45-60	0.03	0.05	0.09	-0.00	0.14**	0.12*	0.02	-0.01	0.01	-0.04
Above 60	0.08	0.07	0.11	0.08	0.20***	0.11	0.00	0.01	0.05	-0.01
<i>Marital Status</i>										
Currently Married	-0.08	-0.09*	0.00	0.07	0.01	-0.08	-0.02	-0.02	0.06	-0.02
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)										
Underweight (BMI< 18.5)	0.00	-0.02	0.03	0.05	0.03	-0.00	0.09**	0.08*	0.09**	0.10**
Overweight (BMI 25-29.9)	-0.10	0.02	0.01	0.01	-0.11	-0.06	0.04	0.12*	-0.00	-0.02
Obese (BMI>30)	-0.05	0.07	-0.19	0.02	-0.20*	-0.08	0.11	0.22*	0.09	0.13
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)										
Q1	0.00	-0.05	-0.06	-0.04	0.02	-0.05	0.05	-0.00	0.03	-0.04
Q2	-0.01	-0.06	-0.09	0.00	-0.05	0.00	0.03	0.08	0.07	0.05
Q4	-0.10	-0.12**	-0.08	0.06	-0.02	-0.02	0.08	0.02	0.09	0.02
Q5	-0.08	-0.04	-0.06	0.05	0.05	0.07	0.07	-0.02	0.07	0.10
Religion (Hindu=1)	-0.04	-0.02	0.01	-0.03	-0.02	0.06	-0.02	0.05	-0.04	0.06
Caste (SC/ST=1)	0.08*	0.11***	-0.04	-0.17***	-0.08*	0.01	-0.02	-0.06	-0.20***	-0.12***
<i>Regional characteristics</i>										
Urban	-0.13**	-0.12**	-0.01	0.05	-0.08	-0.10*	-0.08	-0.02	-0.12**	-0.03
Underdeveloped	-0.37***	-0.09**	-0.25***	-0.21***	-0.10**	-0.10**	-0.42***	-0.23***	-0.36***	-0.30***
Observations	2,771	2,771	2,771	2,771	2,771	2,771	2,771	2,771	2,771	2,771

*** p<0.01, ** p<0.05, * p<0.1

Table 2.2.4: Vignettes set 4: Cognition and Self-care

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Education Categories</i> (Ref category: No formal education)										
Below Primary	-0.12*	-0.09	-0.12*	-0.13*	0.06	0.03	-0.02	0.07	0.01	-0.03
Primary	-0.11*	-0.11*	-0.09	-0.05	0.08	0.02	0.02	0.04	-0.12*	-0.15**
Secondary	-0.13*	-0.05	-0.04	-0.08	-0.09	-0.04	-0.15**	-0.10	-0.01	-0.03
High School	-0.04	-0.01	-0.08	-0.07	0.09	0.11	0.18**	0.15**	0.02	0.04
College and Above	-0.06	-0.08	-0.01	-0.04	0.06	0.10	0.18*	0.16	0.05	-0.03
<i>Individual Characteristics</i>										
Male	0.03	0.01	0.01	-0.09*	-0.12**	-0.19***	-0.16***	-0.19***	0.07	0.02
<i>Age groups</i> (Ref category: Age 18-29.9 years)										
30-44.9	0.05	0.03	0.08	0.09	0.06	0.01	-0.15**	-0.16**	0.11	0.10
45-60	0.11	0.05	0.10	0.08	0.07	0.07	-0.19***	-0.18**	0.13*	0.04
Above 60	0.24***	0.19***	0.18**	0.21***	0.12*	0.15**	-0.14*	-0.12	0.11	0.14**
<i>Marital Status</i>										
Currently Married	-0.06	-0.03	-0.01	0.05	0.08	0.09*	0.05	0.09*	-0.10*	-0.09
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)										
Underweight (BMI<18.5)	-0.00	0.07	0.05	0.04	0.04	0.00	0.01	-0.04	0.10**	0.05
Overweight (BMI 25-29.9)	-0.03	-0.05	-0.02	-0.06	-0.07	-0.03	0.06	0.02	0.01	0.04
Obese (BMI>30)	-0.13	-0.07	-0.13	0.01	0.06	-0.11	-0.09	-0.02	0.01	0.09
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)										
Q1	0.02	-0.01	-0.09	-0.15**	0.03	-0.06	0.06	0.08	-0.04	-0.03
Q2	0.04	0.05	-0.01	-0.09	-0.01	-0.11*	0.09	0.05	-0.06	-0.04
Q4	0.13**	0.09	-0.04	-0.11*	-0.05	-0.05	0.03	0.09	0.07	0.03
Q5	0.13*	0.10	-0.01	0.00	0.13*	0.09	0.11*	0.15**	-0.02	-0.05
Religion (Hindu=1)	-0.07	-0.04	-0.00	-0.06	-0.00	0.05	0.02	0.03	0.03	-0.01
Caste (SC/ ST=1)	0.19***	0.17***	0.01	0.02	0.12***	0.16***	0.13***	0.13***	-0.12***	-0.06
<i>Regional characteristics</i>										
Urban	-0.02	-0.06	-0.11**	-0.11**	0.04	-0.01	0.07	-0.02	-0.01	0.03
Underdeveloped	-0.52***	-0.41***	-0.25***	-0.08*	-0.38***	-0.19***	-0.28***	-0.23***	-0.23***	-0.09**
Observations	2,699	2,699	2,699	2,699	2,699	2,699	2,699	2,699	2,699	2,699

*** p<0.01, ** p<0.05, * p<0.

Table 2.3: Dependent variable: Self reported health

VARIABLES	(1)	(2)	(3)	(4)
Health Today				
<i>Education Categories</i> (Ref category: No formal education)				
Below Primary	-0.10***	-0.09**	-0.07*	-0.07*
Primary	-0.10***	-0.08**	-0.04	-0.03
Secondary	-0.25***	-0.23***	-0.16***	-0.14***
High School	-0.38***	-0.36***	-0.25***	-0.23***
College and Above	-0.63***	-0.60***	-0.46***	-0.44***
<i>Individual Characteristics</i>				
Male	-0.12***	-0.13***	-0.09***	-0.08***
<i>Age groups</i> (Ref category: Age 18-29.9 years)				
30-44.9	0.51***	0.53***	0.50***	0.47***
45-60	0.82***	0.85***	0.76***	0.70***
Above 60	1.18***	1.19***	1.04***	0.91***
<i>Marital Status</i>				
Currently Married	-0.06**	-0.05*	-0.04	-0.03
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)				
Q1	-0.02	-0.04	-0.02	-0.03
Q2	-0.04	-0.05	-0.05	-0.05
Q4	-0.01	0.00	0.02	0.03
Q5	-0.09**	-0.07**	-0.09**	-0.08**
Religion (Hindu=1)	-0.19***	-0.19***	-0.18***	-0.17***
Caste (SC/ST=1)	-0.05**	-0.06***	-0.08***	-0.11***
<i>Regional characteristics</i>				
Urban	-0.11***	-0.10***	-0.10***	-0.08***
Underdeveloped	-0.27***	-0.27***	-0.26***	-0.32***
<i>BMI Categories (measured)</i> (Ref category: Normal bmi 18.5-24.9)				
Underweight (bmi< 18.5)		0.20***	0.17***	0.15***
Overweight (bmi 25-29.9)		0.02	0.00	-0.01
Obese (bmi>30)		0.08	0.01	0.00
Rapid Walk			-0.32***	-0.08
Cognitive score 1			-0.02	-0.02
Cognitive score 2			-0.06***	-0.06***
Cognitive score 3			0.00	0.00
<i>Performance Tests</i>				
Chronic illness			0.25***	0.20***
Lung function			0.00	0.00
Blood Pressure Systolic			0.00	0.00
Blood Pressure Diastolic			0.00	0.00
Pulse rate			0.00***	0.00***
Hearing				0.35***
Vision				0.17***
<i>Interviewer Assessments</i>				
Walking				0.36***
Shortness of breath				0.28***
Overall health problem				0.33***
Observations	10873	10873	10873	10873

Table 2.4: Dependent Variables: Self-reported Functioning measures across various domains of Mobility

Variables	(1)	(2)	(3)	(4)	(5)	(6)
<i>Education Categories</i> (Ref category: No formal education)						
Below Primary	-0.05	-0.07*	-0.02	-0.06	-0.02	-0.02
Primary	-0.06*	-0.05	-0.04	-0.09***	-0.03	-0.09***
Secondary	-0.23***	-0.30***	-0.26***	-0.26***	-0.22***	-0.27***
High School	-0.23***	-0.30***	-0.20***	-0.37***	-0.28***	-0.27***
College and Above	-0.50***	-0.52***	-0.51***	-0.60***	-0.60***	-0.51***
<i>Individual Characteristics</i>						
Male	-0.27***	-0.14***	-0.36***	-0.44***	-0.44***	-0.38***
<i>Age groups</i> (Ref category: Age 18-29.9 years)						
30-44.9	0.48***	0.48***	0.49***	0.35***	0.56***	0.52***
45-60	0.83***	0.84***	0.86***	0.70***	1.00***	0.98***
Above 60	1.27***	01.31***	1.18***	1.09***	1.40***	1.41***
<i>Marital Status</i>						
Currently Married	-0.03	-0.05*	0.02	0.02	-0.01	0.00
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)						
Q1	0.08**	-0.03	-0.01	0.02	0.03	-0.01
Q2	0.06	-0.02	0.06*	0.07*	0.07**	0.05
Q4	0.04	-0.01	-0.03	0.06*	-0.03	-0.01
Q5	0.00	0.03	-0.03	-0.02	0.02	-0.05
Religion (Hindu=1)	-0.12***	-0.13***	-0.11***	-0.14***	-0.12***	-0.16***
Caste (SC/ST=1)	0.14***	-0.06**	0.07***	-0.00	0.11***	0.03
<i>Regional characteristics</i>						
Urban	-0.11***	-0.17***	-0.09***	-0.03	-0.06**	-0.08***
Underdeveloped	-0.18***	-0.04*	-0.22***	-0.33***	-0.22***	-0.06**
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)						
Underweight (BMI< 18.5)	0.08***	0.12***	0.06**	0.07***	0.07***	0.11***
Overweight (BMI 25-29.9)	0.12***	0.06*	0.12***	0.10**	0.15***	0.19***
Obese (BMI>30)	0.27***	0.27***	0.20***	0.30***	0.35***	0.27***
<i>Walk Difficulty</i>						
Timed walk	-0.34	0.22	-0.24	-0.03	-0.35	-0.14
Rapid Walk	-0.36	-0.46*	-0.12	-0.59**	-0.29	-0.43*
Interviewer Assessment	-0.73***	-0.34***	-0.49***	-0.37***	-0.50***	-0.54***
Observations	10,873	10,873	10,873	10,873	10,873	10,873

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications takes value 1-5 measuring self reported difficulty level

(1=no difficulty; 5=extreme difficulty) faced by the respondent in the specific activity describing some form of mobility.

Continuation of Table 2.4: Dependent Variables: Self-reported functioning measures across various domains of Mobility

Variables	(7)	(8)	(9)	(10)	(11)	(12)
<i>Education Categories</i>						
(Ref category: No formal education)						
Below Primary	-0.00	-0.02	-0.06	0.01	-0.08**	-0.04
Primary	-0.08**	-0.07*	-0.10**	-0.08**	-0.10***	-0.21***
Secondary	-0.28***	-0.22***	-0.18***	-0.26***	-0.25***	-0.25***
High School	-0.24***	-0.24***	-0.17***	-0.21***	-0.38***	-0.34***
College and Above	-0.55***	-0.49***	-0.42***	-0.62***	-0.56***	-0.45***
<i>Individual Characteristics</i>						
Male	-0.42***	-0.28***	-0.09***	-0.15***	-0.18***	-0.18***
<i>Age groups</i>						
(Ref category: Age 18-29.9 years)						
30-44.9	0.44***	0.51***	0.35***	0.42***	0.21***	0.44***
45-60	0.80***	1.03***	0.76***	0.77***	0.44***	0.84***
Above 60	1.23***	1.50***	1.19***	1.13***	0.76***	1.15***
<i>Marital Status</i>						
Currently Married	0.02	-0.01	-0.02	-0.09***	-0.14***	0.02
<i>Household's Expenditure Quintiles</i>						
(Ref category: Q3)						
Q1	0.03	0.04	0.12***	0.07**	-0.05	0.06
Q2	0.04	0.04	0.13***	0.06*	-0.04	0.08**
Q4	-0.02	-0.01	-0.07	0.01	-0.02	0.04
Q5	-0.03	-0.03	-0.10**	-0.08**	0.00	-0.06
Religion (Hindu=1)	-0.14***	-0.11***	-0.08**	-0.12***	-0.08**	-0.00
Caste (SC/ST=1)	0.14***	0.08***	0.09***	0.18***	-0.10***	0.13***
<i>Regional characteristics</i>						
Urban	-0.16***	-0.13***	0.03	-0.05*	-0.06**	-0.05
Underdeveloped	-0.34***	-0.20***	-0.05	-0.08***	-0.30***	-0.30***
<i>BMI Categories (measured)</i>						
(Ref category: Normal BMI 18.5-24.9)						
Underweight (BMI< 18.5)	0.11***	0.03	0.06**	0.09***	0.10***	0.04
Overweight (BMI 25-29.9)	0.05	0.17***	0.07	0.04	0.09**	0.09**
Obese (BMI>30)	0.19***	0.32***	0.10	0.14**	0.18***	0.17**
<i>Walk Difficulty</i>						
Timed walk	0.41	0.24	-0.69**	-0.15	0.01	-0.43
Rapid Walk	-0.88***	-0.78***	0.17	-0.36	-0.33	0.19
Interviewer Assessment	-0.36***	-0.46***	-0.29***	-0.39***	-0.37***	-0.52***
Observations	10,873	10,873	10,873	10,873	10,873	10,873

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications takes value 1-5 measuring self reported difficulty level

(1=no difficulty; 5=extreme difficulty) faced by the respondent in the specific activity describing some form of mobility.

Table 2.5: Dependent Variables: Self reported Functioning measures across various domains of Daily Activities

Variables	(1)	(2)	(3)	(4)	(5)	(6)
<i>Education Categories</i> (Ref category: No formal education)						
Below Primary	-0.05	-0.04	-0.06	-0.09**	-0.08**	-0.12**
Primary	-0.09***	-0.16***	-0.16***	-0.12***	-0.09**	-0.12***
Secondary	-0.27***	-0.22***	-0.16**	-0.31***	-0.23***	-0.21***
High School	-0.29***	-0.28***	-0.33***	-0.25***	-0.26***	-0.22***
College and Above	-0.58***	-0.50***	-0.54***	-0.57***	-0.44***	-0.49***
<i>Individual Characteristics</i>						
Male	-0.39***	-0.07*	-0.03	-0.29***	-0.20***	-0.18***
<i>Age groups</i> (Ref category: Age 18-29.9 years)						
30-44.9	0.31***	0.22***	0.38***	0.32***	0.39***	0.35***
45-60	0.70***	0.58***	0.68***	0.73***	0.82***	0.73***
Above 60	1.15***	0.95***	1.00***	1.06***	1.23***	1.11***
<i>Marital Status</i>						
Currently Married	0.03	-0.06	-0.07*	-0.03	-0.06**	-0.02
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)						
Q1	0.03	0.00	0.03	0.01	-0.04	-0.00
Q2	0.02	0.01	-0.04	-0.01	-0.02	0.03
Q4	0.02	-0.02	-0.02	-0.02	0.06*	-0.01
Q5	0.02	-0.03	-0.05	-0.08**	0.02	0.02
Religion (Hindu=1)	-0.18***	-0.14***	-0.15***	-0.17***	-0.16***	-0.10***
Caste (SC/ST=1)	0.06***	0.02	-0.04	0.06**	0.03	-0.01
<i>Regional characteristics</i>						
Urban	-0.07***	0.00	0.00	-0.06**	-0.20***	-0.06*
Underdeveloped	-0.27***	-0.17***	-0.21***	-0.28***	-0.16***	-0.23***
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)						
Underweight (BMI< 18.5)	0.11***	0.15***	0.10***	0.08***	0.13***	0.11***
Overweight (BMI 25-29.9)	0.14***	0.08	0.05	0.02	0.08**	0.10**
Obese (BMI>30)	0.36***	0.20**	0.22**	0.21***	0.26***	0.24***
<i>Walk Difficulty</i>						
Timed walk	0.08	-0.48	-1.00***	0.13	0.39	-0.55*
Rapid Walk	-0.71***	-0.14	0.35	-0.65**	-0.92***	-0.17
Interviewer Assessment	-0.55***	-0.51***	-0.63***	-0.50***	-0.39***	-0.56***
Observations	10,873	10,873	10,873	10,873	10,873	10,873

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications takes value 1-5 measuring self reported difficulty level (1=no difficulty; 5=extreme difficulty) faced by the respondent in the specific activity describing some form of daily activities.

Continuation of Table 2.5: Dependent Variables: Self reported Functioning measures across various domains of Daily Activities

Variables	(7)	(8)	(9)	(10)	(11)
<i>Education Categories</i> (Ref category: No formal education)					
Below Primary	-0.06	0.01	-0.07	-0.05	-0.09**
Primary	-0.19***	-0.17***	-0.18***	-0.14***	-0.19***
Secondary	-0.09*	-0.22***	-0.23***	-0.31***	-0.40***
High School	-0.18***	-0.33***	-0.30***	-0.43***	-0.45***
College and Above	-0.39***	-0.61***	-0.61***	-0.59***	-0.69***
<i>Individual Characteristics</i>					
Male	-0.16***	-0.25***	-0.19***	-0.30***	-0.16***
<i>Age groups</i> (Ref category: Age 18-29.9 years)					
30-44.9	0.34***	0.50***	0.43***	0.31***	0.29***
45-60	0.66***	0.89***	0.76***	0.65***	0.70***
Above 60	1.04***	1.24***	1.14***	1.09***	1.16***
<i>Marital Status</i>					
Currently Married	-0.07**	-0.03	-0.01	-0.05*	-0.05
<i>Household's Expenditure Quintiles</i> (Ref category: Q3)					
Q1	-0.01	0.03	0.06	-0.04	-0.09***
Q2	-0.02	0.06	0.00	0.03	-0.02
Q4	-0.01	-0.00	-0.03	0.00	-0.02
Q5	-0.05	-0.04	-0.12***	-0.05	-0.06*
Religion (Hindu=1)	-0.01	-0.07**	-0.01	-0.09***	-0.11***
Caste (SC/ST=1)	0.03	0.07***	0.07**	0.08***	-0.01
<i>Regional characteristics</i>					
Urban	0.03	-0.09***	-0.10***	-0.11***	-0.01
Underdeveloped	0.25***	-0.30***	0.02	0.15***	0.19***
<i>BMI Categories (measured)</i> (Ref category: Normal BMI 18.5-24.9)					
Underweight (BMI< 18.5)	0.10***	0.07***	0.07**	0.10***	0.12***
Overweight (BMI 25-29.9)	-0.03	0.15***	0.11**	0.10**	0.13***
Obese (BMI>30)	0.06	0.33***	0.27***	0.23***	0.28***
<i>Walk Difficulty</i>					
Timed walk	-0.31	-0.22	-0.55*	-0.26	-0.22
Rapid Walk	-0.04	-0.13	-0.04	-0.46*	-0.44*
Interviewer Assessment	-0.36***	-0.64***	-0.59***	-0.43***	-0.55***
Observations	10,873	10,873	10,873	10,873	10,873

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications takes value 1-5 measuring self reported difficulty level (1=no difficulty; 5=extreme difficulty) faced by the respondent in the specific activity describing some form of daily activities.

Table 2.6: Summary Table of Ordered Probit Regressions with Self reported data

	Positive and Significant	Positive and Insignificant	Negative and Significant	Negative and Insignificant
<i>Education Categories</i>				
(Ref category: No formal education)				
Below Primary	0	2	6	15
Primary	0	0	20	3
Secondary	0	0	23	0
High School	0	0	23	0
College and Above	0	0	23	0
<i>Individual Characteristics</i>				
Male	0	0	22	1
<i>Age groups</i>				
(Ref category: Age 18-29.9 years)				
30-44.9	23	0	0	0
45-60	23	0	0	0
Above 60	23	0	0	0
<i>Marital Status</i>				
Currently Married	0	6	7	10
<i>Household's Expenditure Quintiles</i>				
(Ref category: Q3)				
Q1	3	11	1	8
Q2	6	10	0	7
Q4	2	5	0	16
Q5	0	7	5	11
Religion (Hindu=1)	0	0	20	3
Caste (SC/ST=1)	13	4	2	4
<i>Regional characteristics</i>				
Urban	0	4	16	3
Underdeveloped	3	1	18	1
<i>BMI Categories (measured)</i>				
(Ref category: Normal BMI 18.5-24.9)				
Underweight (BMI< 18.5)	21	2	0	0
Overweight (BMI 25-29.9)	16	6	0	1
Obese (BMI>30)	21	2	0	0
<i>Walk Difficulty</i>				
Timed walk	0	7	4	12
Rapid Walk	0	3	10	10
Interviewer Assessment	0	0	23	0

Table 2.7: Dependent Variable: Self reported Cognitive difficulty

VARIABLES	(1)	(2)
Self reported cognition	Memory	Concentration
<i>Education Categories</i>		
(Ref category: No formal education)		
Below Primary	-0.12***	-0.11***
Primary	-0.09**	-0.10***
Secondary	-0.30***	-0.33***
High School	-0.38***	-0.42***
College and Above	-0.52***	-0.69***
<i>Individual Characteristics</i>		
Male	-0.18***	-0.07**
<i>Age groups</i>		
(Ref category: Age 18-29.9 years)		
30-44.9	0.53***	0.48***
45-60	0.88***	0.81***
Above 60	1.22***	1.23***
<i>Marital Status</i>		
Currently Married	-0.08***	-0.08***
<i>Household's Expenditure Quintiles</i>		
(Ref category: Q3)		
Q1	-0.00	-0.02
Q2	-0.01	-0.01
Q4	0.03	-0.00
Q5	-0.01	-0.03
Religion (Hindu=1)	-0.15***	-0.05
Caste (SC/ST=1)	0.01	-0.01
<i>Regional characteristics</i>		
Urban	-0.23***	-0.13***
Underdeveloped	-0.10***	-0.10***
<i>Cognitive tests</i>		
Cognitive Score 1	-0.04***	-0.04***
Cognitive Score 2	-0.08***	-0.07***
Words recalled	-0.03***	-0.02***

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in both the specifications takes value 1-5 measuring self reported difficulty level

(1=no difficulty; 5=extreme difficulty) faced by the respondent in remembering and concentrating things

Objective measures include (test of words recalled after delay, digital recall test and verbal fluency)

Table 2.8: Dependent Variable: Objective Memory and Cognitive tests

VARIABLES	(1)	(2)	(3)
Objective memory tests	Words recalled	Score1	Score2
<i>Education Categories</i>			
(Ref category: No formal education)			
Below Primary	0.24***	0.43***	0.51***
Primary	0.39***	0.71***	0.78***
Secondary	0.57***	0.94***	1.11***
High School	0.80***	1.22***	1.46***
College and Above	0.98***	1.55***	1.84***
<i>Individual Characteristics</i>			
Male	-0.07***	0.31***	0.40***
<i>Age groups</i>			
(Ref category: Age 18-29.9 years)			
30-44.9	-0.25***	-0.21***	-0.20***
45-60	-0.56***	-0.42***	-0.34***
Above 60	-0.85***	-0.63***	-0.49***
<i>Marital Status</i>			
Currently Married	0.08***	0.07***	0.05*
<i>Household's Expenditure Quintiles</i>			
(Ref category: Q3)			
Q1	-0.12***	-0.10***	-0.03
Q2	-0.05	-0.06*	-0.03
Q4	0.04	0.03	0.08**
Q5	0.12***	0.14***	0.20***
Religion (Hindu=1)	0.04	-0.02	-0.05*
Caste (SC/ST=1)	-0.01	-0.13***	-0.08***
<i>Regional characteristics</i>			
Urban	0.16***	0.09***	0.15***
Underdeveloped	0.11***	-0.11***	-0.23***

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications are objective measures of Memory and Cognition including

(test of words recalled after delay, digital recall test and verbal fluency.)

Table 2.9: Dependent Variable: Objective measures of difficulty in Mobility and General health

Objective Mobility Measures	(1) Assessed Walk	(2) Assessed Walk	(3) Assessed Health	(4) Assessed Health
<i>Education Categories</i>				
(Ref category: No formal education)				
Below Primary	-0.11	-0.11	-0.03	-0.04
Primary	-0.12	-0.13*	-0.02	-0.03
Secondary	-0.16*	-0.16*	-0.23***	-0.24***
High School	-0.31***	-0.32***	-0.11**	-0.12**
College and Above	-0.29**	-0.31**	-0.17**	-0.18***
<i>Individual Characteristics</i>				
Male	0.08	0.09*	-0.13***	-0.12***
<i>Age groups</i>				
(Ref category: Age 18-29.9 years)				
30-44.9	0.32**	0.31*	0.26***	0.25***
45-60	0.79***	0.77***	0.47***	0.45***
Above 60	1.34***	1.32***	0.73***	0.72***
<i>Marital Status</i>				
Currently Married	-0.12**	-0.12**	-0.00	-0.00
<i>Household's Expenditure Quintiles</i>				
(Ref category: Q3)				
Q1	0.08	0.08	-0.05	-0.05
Q2	-0.06	-0.06	-0.04	-0.04
Q4	-0.02	-0.02	-0.09**	-0.09**
Q5	-0.16**	-0.16**	-0.08*	-0.09**
Religion (Hindu=1)	-0.01	-0.00	-0.02	-0.02
Caste (SC/ST=1)	0.06	0.06	0.22***	0.22***
<i>Regional characteristics</i>				
Urban	0.01	0	-0.11***	-0.12***
Underdeveloped	0.53***	0.53***	0.14***	0.14***
Underweight		0.07		0.03
Overweight		0.15*		0.15***
Obese		0.32**		0.17**
Observations	10,873	10,873	10,873	10,873

*** p<0.01, ** p<0.05, * p<0.1

The dependent variables in all the specifications are interviewer assessed difficulty (dummy variable) in Mobility and General health

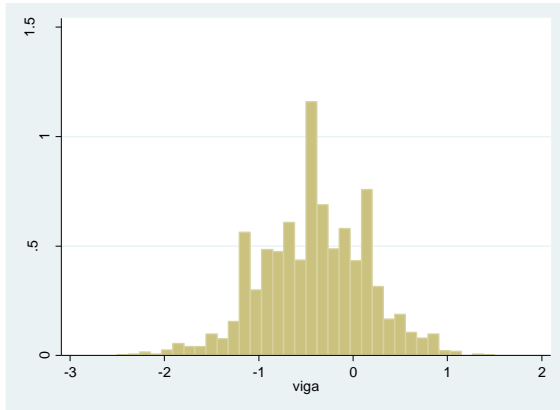
Specification (2) and (4) controls for body mass index categories.

Table 2.10: Estimations of two-stage regressions using individual fixed effects

VARIABLES	(1) Vignette Set A	(2) Vignette Set B	(3) Vignette Set C	(4) Vignette Set D
<i>Education Categories</i>				
Below Primary	0.02	-0.03	0.04	-0.11
Primary	0.00	-0.05	-0.05	-0.10*
Secondary	-0.01	-0.02	0.03	-0.11*
High School	0.00	-0.01	-0.01	-0.03
College and Above	0.01	-0.02	0.11**	-0.05
<i>Individual Characteristics</i>				
Male	-0.08***	-0.01	-0.07***	0.03
<i>Age groups</i>				
30-44.9	0.05	0.03	0.00	0.04
45-60	0.02	-0.01	0.04	0.10
Above 60	0.11***	-0.01	0.07*	0.21***
<i>Marital Status</i>				
Currently Married	-0.01	-0.06**	-0.02	-0.05
<i>BMI Categories (measured)</i>				
Underweight (bmi< 18.5)	-0.01	0.02	0.04*	0.00
Overweight (bmi 25-29.9)	-0.02	-0.01	-0.01	-0.03
Obese (bmi>30)	0.05	-0.05	0.01	-0.12
<i>Household's Expenditure Quintiles</i>				
Q1	-0.16***	-0.07**	-0.01	0.02
Q2	-0.08**	0.01	0.01	0.03
Q4	-0.11***	0.01	-0.00	0.11*
Q5	-0.05	-0.01	0.02	0.11*
Religion (Hindu=1)	-0.04	-0.01	-0.00	-0.06
Caste (SC/ST=1)	0.08***	-0.01	-0.05**	0.17***
<i>Regional characteristics</i>				
Urban	-0.06**	-0.02	-0.06**	-0.02
Underdeveloped	-0.09***	-0.12***	-0.22***	-0.47***
Constant	-0.29***	-0.16***	-0.44***	2.45***
Observations	2,673	2,728	2,770	2,698
R-squared	0.03	0.02	0.04	0.07

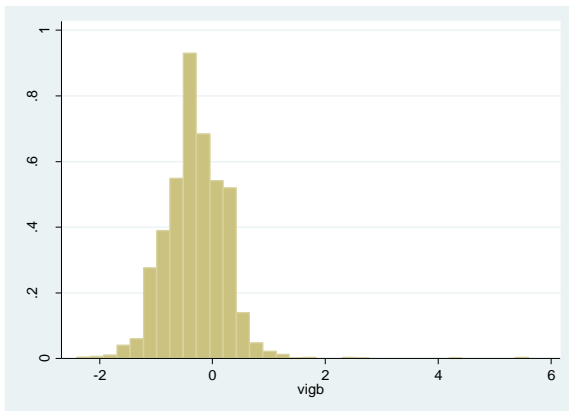
*** p<0.01, ** p<0.05, * p<0.1

Figure 2.9: Distribution of estimated coefficients for individual reporting from Vignette set A



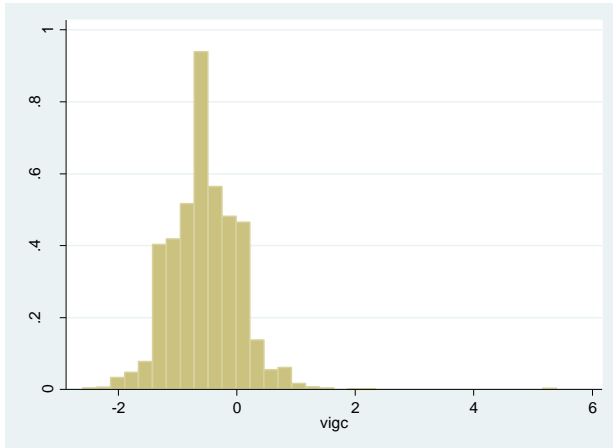
Note: Health domains in set A includes Mobility and Affect

Figure 2.10: Distribution of estimated coefficients for individual reporting from Vignette set B



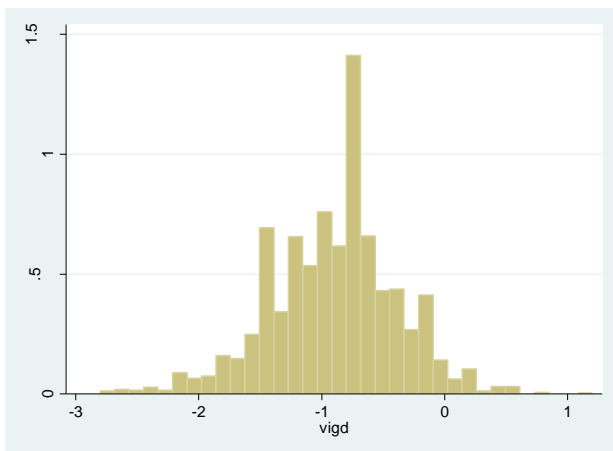
Note: Health domains in set B includes Pain and Personal Relationships

Figure 2.11: Distribution of estimated coefficients for individual reporting from Vignette set C



Note: Health domains in set A includes Vision, Sleep and Energy

Figure 2.12: Distribution of estimated coefficients for individual reporting from Vignette set D



Note: Health domains in set A includes Cognition and Self-Care

2.A Appendix

List of five sample vignettes from each health domain in WHS-SAGE Survey questionnaire

Set A Affect and Mobility

[Alan] is able to walk distances of up to 200 metres without any problems but feels tired after walking one kilometre or climbing up more than one flight of stairs. He has no problems with day-to-day physical activities, such as carrying food from the market.

[Manjima] enjoys her work and social activities and is generally satisfied with her life. She gets depressed every 3 weeks for a day or two and loses interest in what she usually enjoys but is able to carry on with her day to day activities.

[Miriam] does not exercise. She cannot climb stairs or do other physical activities because she is obese. She is able to carry the groceries and do some light household work.

[Vladimir] is paralyzed from the neck down. He is unable to move his arms and legs or to shift body position. He is confined to bed.

[Ang] has already had five admissions into the hospital because she has attempted suicide twice in the past year and has harmed herself on three other occasions. She is very distressed every day for the most part of the day, and sees no hope of things ever getting better. She is thinking of trying to end her life again.

Set B Pain and Personal Relationships

[Elizabeth] has difficulty climbing up and down the stairs and walking. She is not able to go out as much as she would like to but has many friends who come and visit her at home. Her friends find her a source of great comfort.

[Markus] has pain in his knees, elbows, wrists and fingers, and the pain is present almost all the time. It gets worse during the first half of the day. Although medication helps, he feels uncomfortable when moving around, holding and lifting things.

[Nobu] is blind and lives in a remote rural area. His family does not allow him to leave the house because they fear he will get hurt. His family tells him that he is a burden to them. Their criticism upsets him and he cries.

[Laura] has a headache once a month that is relieved one hour after taking a pill. During the headache she can carry on with her day to day affairs.

[Isabelle] has pain that radiates down her right arm and wrist during her day at work. This is slightly relieved in the evenings when she is no longer working on her computer.

Set C Vision, Sleep and Energy

[Damien] wakes up almost once every hour during the night. When he wakes up in the night, it takes around 15 minutes for him to go back to sleep. In the morning he does not feel well-rested and feels slow and tired all day.

[Antonio] can read words in newspaper articles (and can recognize faces on a postcard size photograph). He can recognize shapes and colours from across 20 metres but misses out the fine details.

[Paolo] has no trouble falling asleep at night and does not wake up during the night, but every morning he finds it difficult to wake up. He uses an alarm clock but falls back asleep after the alarm goes off. He is late to work on four out of five days and feels tired in the mornings.

[Jennifer] only reads if the text is in very large print, such as 10 lines per page. Otherwise she does not read anything. Even when people are close to her, she sees them blurred.

[Noemi] falls asleep easily at night, but two nights a week she wakes up in the middle of the night and cannot go back to sleep for the rest of the night. On these days she is exhausted at work and cannot concentrate on her job.

Set D Cognition and Self-Care

[Anne] takes twice as long as others to put on and take off clothes, but needs no help with this.

Although it requires an effort, she is able to bathe and groom herself, though less frequently than before. She does not require help with feeding.

[Sue] can find her way around the neighborhood and know where her own belongings are kept, but struggles to remember how to get to a place she has only visited once or twice. She is keen to learn new recipes but finds that she often makes mistakes and has to reread several times before she is able to do them properly.

[Theo] cannot concentrate for more than 15 minutes and has difficulty paying attention to what is being said to him. Whenever he starts a task, he never manages to finish it and often forgets what he was doing. He is able to learn the names of people he meets but cannot be trusted to follow directions to a store by himself.

[Sandra] lives on her own and has no relatives or friends nearby. Because of her arthritis, she is housebound. She often stays all day in the same clothes that she has slept in, as changing clothes is too painful. A neighbour helps her wash herself.

[Victor] requires no assistance with cleanliness, dressing and eating. He occasionally suffers from back pain and when this happens he needs help with bathing and dressing. He always keeps himself tidy.