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Health Shocks and Coping Strategies: State Health Insurance Scheme of Andhra Pradesh, India

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Abstract

The objectives of the study are three-fold: to investigate who are vulnerable to welfare loss from health shocks, what are the household responses to cope with the economic burden of health shocks and if policy responses like state health insurance schemes are effective in reducing the economic vulnerability. Existing literature have investigated the impact of state health insurance schemes in reducing the vulnerability to financials risks of medical care using catastrophic health expenditure (CHE) measure. This has several limitations like setting arbitrary threshold levels, exclusion of those that did not seek medical care due to inability to pay and non-accounting for risks posed by different sources of financing. So we use self-reported measure of reduction in economic well-being of households due to serious illness or death of one or more members from the recent Young Lives longitudinal study in Andhra Pradesh, India. Three-level random intercept logistic regression analysis that accounts for role of contextual or environmental factors like access to healthcare is used to determine the characteristics of vulnerable population and effectiveness of the state insurance scheme.

Keywords: *Health shocks, coping strategies, state health insurance scheme, three-level random intercept model*
JEL Codes*: I10, I13*

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However, I am solely responsible for all the views expressed. The views are not necessarily of any of the organizations or persons mentioned here.

INTRODUCTION

The impact of income shocks on households in low and middle-income countries has received much attention in development economics literature. This is because income shocks like weather and price variability are important factors associated with movements of households in and out of poverty (Morduch, 1994). They also affect the health and nutrition status of household members (Foster, 1995), alter households' investments in human capital (Jacoby and Skoufias, 1997), influence their livelihood strategies and welfare trajectories (Ellis, 1998) etc. Some of these shocks are covariate in nature - common to all households in a community - like drought and flood while others are idiosyncratic in nature- specific to individual households like job loss and illness. This study deals with understanding the factors that lead to household welfare loss from a particular type of idiosyncratic shock, namely health shock.

Health shock is the most common idiosyncratic shock and the most important reason for descent of households into poverty in developing countries (Krishna, 2007). A household is said to face a health shock when an illness or injury weakens the health status of its member and generates a welfare loss for the household[1] (Khan, 2010). Such shocks involve direct and indirect costs. Direct costs are expenditures incurred on those goods and services during medical care like hospitalization and outpatient treatment, drugs and medical supplies. Indirect costs refer to the loss of productive labour time and thus labour earnings of patients as well as caregivers. Due to non-existent or imperfect credit and insurance markets in developing countries, households rely on different informal mechanisms like transfers from family and friends, sale of assets and borrowing from moneylenders to cope with the economic costs of health shocks. Despite these coping

[1] Though health shocks affect individuals, the unit of analysis is household. This is because decisions regarding medical expenditure and coping strategies are based on negotiations within the household and the burden of medical costs falls on the household budget (Russell, 2004).

mechanisms, households remain vulnerable to welfare disruptions and impoverishment (Dercon, 2002).

In a seminal work, Gertler and Gruber (2002) find that Indonesian households are not able to insure consumption during severe health crises. The ability of the households to smooth consumption against health shocks depends on severity of the health shocks (Cochrane, 1991), employment status of members facing health shocks (Kochar, 1995), household resources like human and physical capital (Gertler and Gruber, 2002), access to financial markets (Islam and Maitra, 2012) etc. Health shocks are also found to have an adverse impact on education attainment and nutritional status of household members (Dercon and Krishnan, 2000; Sun and Yao, 2010). Thus, the knowledge of who are vulnerable to welfare loss from health shocks and coping strategies is very important from policy perspectives.

Existing literature have investigated the vulnerability to financials risks of medical care and the impact of policy instruments like state health insurance scheme in reducing this risk using catastrophic health expenditure (CHE) measure. A household is said to have incurred CHE if the proportion of OOP health expenditure in household income or total expenditure crosses some threshold level, say, 5 percent, 10 percent or 20 percent. This measure has several limitations like setting arbitrary threshold levels, exclusion of those that did not seek medical care due to inability to pay and non-accounting for risks posed by different sources of financing. Hence we use self-reported reduction in household welfare due to health shocks as an outcome measure.[2] Similarly, studies on coping

[2] A self-reported measure of economic burden due to health shocks complements existing empirical studies that use CHE measure by taking into account: 1) inability to pay for healthcare, 2) direct as well as indirect costs of health shocks, 3) different capacity of each household to cope with financial risks associated with different sources of financing healthcare. There are also other studies that use similar self reported measures in different contexts: household welfare affected due to illness (Sparrow *et. al.*, 2012), health shocks impacted household well-being (Wagstaff and Lindelow, 2014), household faced big expenditure/income loss (self-perceived) due to illness (Islam and Maitra, 2012) etc.

strategies adopted for health shocks have only examined factors leading to distress financing (borrowing or selling assets) for medical expenditure. Health shocks are more likely to prompt households to seek assistance or transfers from friends, extended family etc. (Wagstaff and Lindelow, 2010). There are also households that do not have access to either informal support networks or formal credit and insurance markets. Such households resort to reduction of current consumption or sending children or other members of the family to work to cope with the costs of medical care and income loss[3].

This study focuses on the southern state of Andhra Pradesh which launched *Rajiv Arogyasri* (RAS) public health insurance scheme in 2007. We use longitudinal data of *Young Lives* project that studies childhood poverty in four countries and has information on whether households faced reduction in economic welfare (self-perceived) due to serious illness or death of one or more members. We empirically investigate the following questions: 1) What are the factors that lead to welfare loss (as self-perceived by households) from health shocks? 2) What is the likelihood of adopting risk-coping strategies like borrowing, selling assets and reducing consumption when households face health shocks? 3) How effective is the state health insurance scheme of Andhra Pradesh in reducing the welfare loss from health shocks? We find that economic vulnerability to health shocks and coping strategies is high among poorer households, those with elderly and chronically ill and disabled members, SC and Muslim households. The state insurance scheme does not provide adequate protection from economic losses of health shocks and we further explore the reasons behind this.

This study is organized as follows. The following sections describe the conceptual framework and the longitudinal dataset used in

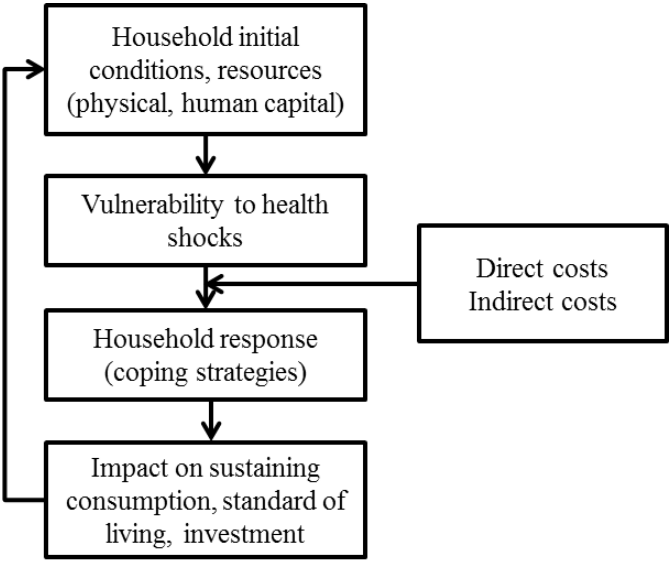
[3] Few studies like Binnendjik *et. al.* (2012) and Qunitussi *et. al.*, (2015) have analysed the determinants of mechanisms through which households cope with high cost medical expenditure in the Indian context. Damme *et. al.* (2004) Kruk *et. al.* (2009), Nguyen *et. al.* (2012) etc. have done similar analysis in other countries context.

this study. Following this, I explain the methodology used in this study. Results of the analysis and sum-up are given in the final sections.

Conceptual Framework

A description of the conceptual framework used in the study is given below (Figure 1). Household initial conditions, resources, demographic characteristics etc. affect its economic vulnerability to health shocks (Bird and Prowse, 2008). When one or more members of the household faces health shock, it decides whether to seek medical care based on the economic costs of illness as well as its own perceptions. Those that do not seek medical care may face further severity of illness or death leading to future welfare loss. Those that seek medical care may face both direct and indirect costs. Direct costs depend on type of treatment (outpatient or inpatient) and type of service provider (public or private) sought by the households as well as coverage under insurance. Indirect costs depend on whether working members of the household have protection against loss in income due to absence from work. Based on these costs and available resources, households decide on the coping strategies to sustain current levels of consumption. In such a pursuit, households may deplete their resources that increase their vulnerability to future shocks.

Figure 1: Conceptual Framework



Data and Summary Statistics

We use the longitudinal dataset of *Young Lives* project that aims to study childhood poverty over a span of 15 years in four countries (Ethiopia, India, Peru and Vietnam) through household and child surveys. In India, the survey is conducted in the state of Andhra Pradesh and three rounds have been completed (2002, 2006 and 2009). The sample consists of two age-groups of children: younger cohort of 2011 children born in 2001-02 and older cohort of 1008 children born in 1994-95. The attrition rate from Round 1 to Round 3 is 3.6 percent; it is 2.2 percent if attrition due to child-deaths is excluded (Galab *et. al.*, 2011). The sampling method used in the survey is as follows: Andhra Pradesh has three agro-climatic regions – Telangana, Rayalaseema and Coastal Andhra. One poor and one non-poor district were chosen from each region[4] and twenty sentinel sites (*taluk*) were then chosen from these districts. Those households

[4] Poor and non-poor districts and mandals were selected based on a set of development indicators. In addition to the six districts, Hyderabad district, capital of Andhra Pradesh was also included. For details of the sampling method, refer to Galab *et. al.* (2011).

with a child born in 2001-02 (numbering 100) and those with a child born in 1994-95 (numbering 50) were randomly selected from each sentinel site.

This longitudinal dataset gives a profile of households' assets, livelihoods and socio-economic characteristics. It also has rich information on income shocks and the type of responses to these shocks. The study asked sample households if they faced any income shock that affected the economy of the household negatively or reduced the economic welfare[5]. Table 1 gives the percent age of households that were affected by income shocks during the few years preceding the three rounds of survey. The percent age of households that reported being affected by income shocks is higher in Round 2 because it covered a longer recall period (4 years compared to 2 years and 2.5 years for Round 1 and Round 3 respectively). In the case of Round 1, percent age of households reporting income shocks is much higher for the older cohort compared to the younger cohort since the recall period was nine years for the former while two years for the latter (shocks affecting the household since the birth of *Younglives* child). Crop loss and natural disasters like flood and drought are the major shocks that caused reduction in economic well-being of households. Health shock is the next major shock affecting 6-7 percent of the households on an average every year.

[5] Table I in Appendix gives detailed information on questions asked in each of rounds.

Table 1: Income Shocks Faced by Households

Type of shocks	Between child birth and Round 1 (percent)		Between Round 1 and Round 2 (percent)		Between Round 2 and Round 3 (percent)	
	Younger	Older	Younger	Older	Younger	Older
Serious illness / death	18.55	27.38	28.67	31.79	18.20	20.71
Theft / fire / eviction	5.87	5.65	9.44	7.95	6.00	4.26
Job loss / Education expenses	7.96	14.48	3.64	4.12	1.38	1.12
Livestock loss / disease	5.82	8.04	6.31	7.75	7.64	9.34
Crop loss / damage	28.19	32.74	18.15	21.63	21.32	22.34
Natural disasters	22.28	24.11	30.56	31.19	9.58	11.27
Price fluctuations			11.13	11.27	78.58	74.72
Others	0.10	0.14	2.92	4.23	8.82	9.54
Observations	2011	1008	1950	994	1951	985

Source: Based on the author's calculation from unit level data of *Young Lives* survey.

The coping strategies used by the households that faced health shocks are reported in Table 2.[6] Only summary statistics of Round 2 and Round 3 are reported here. This is because the Round 1 survey recorded the coping strategies against health shocks only when health shock was reported to be one among the three most important economic shocks for the household. One-third of the households depended on credit to cope with the economic burden of serious illness/death of household

[6] The survey gives the first three responses of the household to reduction in economic well-being due to serious illness/death episode. However, only the most important strategy adopted by the household is used in this study.

members. The next important strategy used to cope with health shocks is transfers from friends, family, neighbours etc. This accounted for nearly one-fourth of all responses. Around 10 percent of the households used their own savings to cope with economic costs of illness in Round 2 and this increased to more than 15 percent in Round 3. Around 5 percent of the households worked more to bear the costs of health shocks (by sending children or other members of the family to work) while 3 percent reduced their consumption expenditure.

Table 2: Households' Responses to Economic Costs of Health Shocks

Household response	Between Round 1 and Round 2		Between Round 2 and Round 3	
	Younger (percent)	Older (percent)	Younger (percent)	Older (percent)
Ate less	0.59	2.15	1.19	0.41
Bought less	2.38	2.96	2.63	2.46
Migrated to find work	1.93	2.42	0.95	0.41
Nothing	17.68	13.44	8.35	0.82
Received help from the community	2.08	4.03	2.39	8.61
Received help from relatives/friends	20.51	18.55	20.05	20.08
Received help from government/NGO	1.04	0.27	2.39	3.69
Sent children to be cared for by friend	0.74	0.54	0.72	1.23
Sent children to work	0.15	1.34	0.24	0.41
Sold possessions/belongings	0.74	0.81	0.48	1.23
Took children out of school	0.15	1.34	0.24	0.41
Used credit	34.32	33.87	30.55	32.79
Used savings	10.4	7.8	16.47	15.57
Worked more	4.9	7.26	7.4	6.97
Mortgaged	0.15	0.27	1.91	1.23
Fled/moved away from problem	0.45	0.81		
Sold animals			1.43	1.23
Started looking for job			0.48	0.41
Sold properties			0.72	
Others	1.78	1.88	1.43	2.05

Source: Based on the author's calculation from unit level data of *Young Lives* survey.

Methodology

This study uses logistic regression analysis as the outcomes of interest (health shocks faced by households and the coping strategies used) are categorical variables. The panel logit model using a latent variable framework is as follows:

$$y_{ij}^{*} = \alpha + h_j + \boldsymbol{x}_{ij}\boldsymbol{\beta} + u_{ij}$$
$$y_{ij} = 1\left[y_{ij}^{*} > 0\right]$$
$$y_{ij} = 0\left[y_{ij}^{*} \leq 0\right] \quad (1)$$

and

$$\Pr\left(y_{ij} = 1 \mid \boldsymbol{x}_{ij}, h_j\right) = G\left(\alpha + h_j + \boldsymbol{x}_{ij}\boldsymbol{\beta}\right) \quad (2)$$

where i refers to the measurement occasions or round of the panel survey $(i = 1,2,3)$ and j refers to the household $(j = 1, 2, 3..J)$, y_{ij}^{*} is a latent variable, y_{ij} is the binary response variable, $\boldsymbol{x}_{ij}$ is $1 \times n$ vector of observed covariates, $\boldsymbol{\beta}$ is $n \times 1$ vector of parameters, h_j is an unobserved time invariant household effect, and u_{ij} is a zero-mean residual. $G\left(\alpha + h_j + \boldsymbol{x}_{ij}\boldsymbol{\beta}\right) = \frac{exp(\alpha + h_j + \boldsymbol{x}_{ij}\boldsymbol{\beta})}{1 + exp(\alpha + h_j + \boldsymbol{x}_{ij}\boldsymbol{\beta})}$ is the logisitic cumulative distribution function.

There are different methods for estimation of logit model with panel data: (1) complete pooling, (2) unconditional fixed effects, (3) conditional fixed effects, and (4) random effects (Bartels, 2008). Under the complete pooling models, it is assumed that there are no individual unobserved effects (i.e., $h_j = 0$) thus ignoring the panel structure of the data. In this method, $\boldsymbol{\beta}$ coefficients are the same as those obtained from standard cross-section models but the standard errors are corrected to account for correlation within individuals. A disadvantage of this method is that ignoring unobserved heterogeneity can induce omitted variable bias. In the case of linear regression models, h_j can be eliminated by first-differencing or transformation. But this is not possible in the case of

non-linear (logit) models. In unconditional fixed effect approach, h_j is estimated directly by adding dummy variables for $J-1$ individuals. But this may lead to incidental parameters problem: in the maximum likelihood method, if some parameters are not consistent, then all estimators become inconsistent. Thus, with small number of measurement occasions (here, $I=3$) and large J, h_j will not be consistent which in turn renders the estimates of $\boldsymbol{\beta}$ to be inconsistent.

The unobserved heterogeneity at household level can also be taken into account through conditional fixed effects logit or traditional random effects model. In the conditional fixed effects approach, individual effects h_j disappear from the likelihood by conditioning on the total number of successes (minimum sufficient statistic)[7]. For instance, when $I=2$, we condition on $y_{1j}+y_{2j}=1$. The possible sequences are $\{1,0|0,1\}$. When $I=3$, we condition on $y_{1j}+y_{2j}+y_{3j}=1$ $\{1,0,0|0,1,0|0,0,1\}$ or $y_{1j}+y_{2j}+y_{3j}=2$ $\{1,1,0|0,1,1|1,0,1\}$. Thus only those individuals whose responses vary across time periods are used in the estimation. In the traditional random effects model, h_j is assumed to follow normal distribution ($h_j \sim N(0,\sigma_h^2)$). Usually h_j is integrated out of the likelihood and numerical methods like quadrature are used to estimate the coefficients as there is no analytical solution here.

Maddala (1987) lists the following disadvantages of using fixed effects approach. It uses within-individual differences and hence gives inefficient estimates if within individual variation is low. Also, the fixed effects approach cannot be used to estimate the effects of covariates that do not change over time like gender and race as those are captured by h_j. The random effects approach only estimates the variance of h_j thus saving a lot of degrees of freedom compared to fixed effects. Moreover, for large number of individuals and small number of

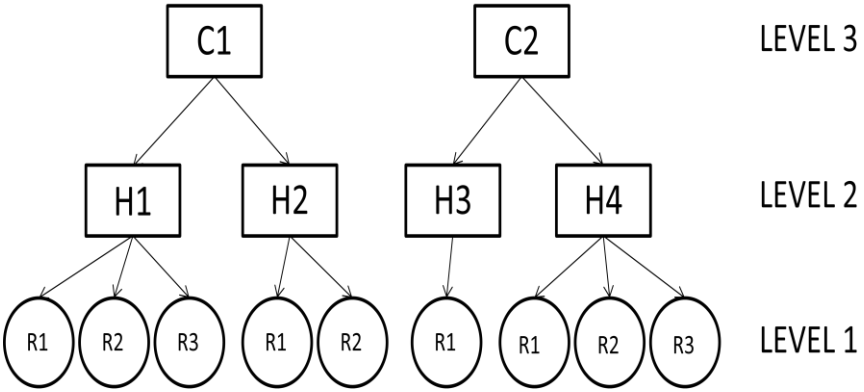
[7] The conditional ML method is difficult to estimate for probit link function as these effects do not cancel out.

measurement occasions, fixed effects method gives rise to inconsistent estimates due to incidental parameters problem. Thus we use random effects logit model to answer the questions mentioned in Section 2[8].

Further, contextual or environmental factors like access to healthcare and average living standards of the community play an important role in influencing health shocks faced by households within a cluster, i.e., geographical area (Gibbons and Hedekar, 1997). Thus, the outcomes of households within a cluster are more likely to be correlated than that of households between clusters. Usually, this is accounted for by relaxing the assumption of independence between households within the same cluster and correcting for intra-cluster correlation in the standard error formula. In addition, studies also include relevant group-level covariates or dummies along with household-level covariates in a single model. However this leads to treating data at higher level as independent information from much larger sample of lower-level units which gives rise to spurious results. We overcome these problems using multi-level modeling. Since *Young Lives* project randomly selected 150 households each from 20 different clusters (taluk), we expect that the outcomes of households from the same cluster are correlated. We take into account this unobserved heterogeneity at the cluster level in addition to that at the household level by specifying a three-level random intercept model. The three levels are measurement occasions at the first level (denoted by Rounds - R1, R2 or R3 in Figure 2), household at the second level (H) and taluk or cluster at the third level (C).

[8] The random effects model assumes that unobserved heterogeneity $h_j$is independent of the covariates, $\boldsymbol{x}_{ij}$. We test for correlation between time-varying covariates and h_j using Chamberlain correlated random effects method and do not find it to be significant.

Figure 2: Three-Level random effects models



The three-level random intercept model using latent variable formulation is written as follows:

$$y_{ijk}^{*} = \alpha + h_{jk} + c_k + \boldsymbol{x}_{ijk}\boldsymbol{\beta} + \boldsymbol{x}_{jk}^{'}\boldsymbol{\beta}^{'} + \boldsymbol{x}_{k}^{''}\boldsymbol{\beta}^{''} + \varepsilon_{ijk}$$

$$h_{jk} \sim N(0, \sigma_h^2);\ c_k \sim N(0, \sigma_c^2)$$

$$y_{ijk} = 1\left[y_{ijk}^{*} > 0\right]$$

$$y_{ijk} = 0\left[y_{ijk}^{*} \leq 0\right]$$

$$\Pr\left(y_{it} = 1 \mid \boldsymbol{x}_{ijk}, \boldsymbol{x}_{jk}^{'}, \boldsymbol{x}_{k}^{''}, h_{jk}, c_k\right) = G\left(\alpha + h_{jk} + c_k + \boldsymbol{x}_{ijk}\boldsymbol{\beta} + \boldsymbol{x}_{jk}^{'}\boldsymbol{\beta}^{'} + \boldsymbol{x}_{k}^{''}\boldsymbol{\beta}^{''} + c_i\right) \quad (3)$$

where i refers to the measurement occasions $(i = 1,2,3)$ and j refers to the household $(j = 1,2 \ldots J)$, k refers to the cluster or taluk $(k = 1,2 \ldots 20)$, y_{ijk}^{*} is a latent variable, y_{ijk} is binary response variable, $\boldsymbol{x}_{ijk}$ is $1 \times n_1$ vector of time-varying covariates at the household level, $\boldsymbol{x}_{jk}^{'}$ is $1 \times n_2$ vector of time-invariant covariates at the household level, $\boldsymbol{x}_k$ is $1 \times n_3$ vector of covariates at the cluster level, $\boldsymbol{\beta}$, $\boldsymbol{\beta}^{'}$ are $\boldsymbol{\beta}^{''}$ are $n_1 \times 1$, $n_2 \times 1$, $n_3 \times 1$ vectors of parameters respectively, h_{jk} is an unobserved time invariant household effect and c_k the unobserved cluster effect, ε_{ijk} is a zero-mean residual and $G(\cdot)$ is the cumulative logisitic distribution function. Here the regression coefficients α, $\boldsymbol{\beta}$, $\boldsymbol{\beta}^{'}$ and $\boldsymbol{\beta}^{''}$ are called fixed effects since they do not vary across levels while

h_{jk} and c_k are called the random intercepts. The following sections detail on the variables used in the model.

Economic Vulnerability to Health Shocks

The first three rounds of the *Young Lives* survey are pooled to determine the factors that lead to welfare loss from health shocks. The dependent variable is binary that takes value 1 if the household faced health shock that reduced the economic welfare of the household and 0 otherwise. The independent variables are classified into household head characteristics, demographic, socio-economic and community characteristics[9]. The characteristics of household head include age, gender, education level and working status[10]. We hypothesize that households with educated and regular salaried head are less likely to face reduction in well-being due to health shocks and that vulnerability to health shocks increases with age of the household head. The socio-economic characteristics that are taken into consideration are wealth quartile group, caste and religious groups that households belong to. Wealthier households have more resources to cope with economic costs of health shocks and hence face lower probability of welfare loss. It is posited that households belonging to SC and ST categories are more vulnerable to health shocks due to their low socio-economic status compared to other groups in general. The demographic characteristics like dependency ratios and presence of elderly and disabled members are other explanatory variables used. We hypothesise that households with elderly and chronically-ill member face more illness episodes and hence higher economic costs. A dummy variable indicating if the household was covered by Rajiv Arogyasri health insurance scheme was included to

[9] Refer Table III in the Appendix for summary statistics

[10] The nature of the job undertaken by the head was not controlled for due to issues with data consistency across rounds. Round 1 survey gives information on sector (agriculture, manufacturing, mining etc) in which the household head works while Round 2 and Round 3 survey has information on nature of the job (self-employed, regular-salaried, casual labourer etc.) only.

investigate the role of the public insurance scheme in reducing the economic burden of health shocks[11].

Coping Strategies

The second and third rounds of the *Young Lives* survey are pooled to determine the likelihood of adopting different coping strategies when health shocks affect one or more household members. The first round was not included as households' responses were only available for the three most important economic shocks as previously mentioned in Section 5. The coping strategy used by the household are grouped into six categories (1-savings, 2- receive help, 3-credit or sale of assets, 4-take more work, 5-reduce expenditure and 6-others[12]) as shown in Table II in the Appendix. Three-level multinomial logistic regression analysis is used for investigating the determinants of coping strategies adopted by households that faced health shocks. Here the unit of analysis is at the household member level. This is because coping strategies used might differ across members of the household and also more than one member of the household may face health shock in a given period.

The independent variables used in the analysis are categorized into individual, household and community level factors. In order to determine if there are differences in coping strategies used among the

[11]Dummy variables for each round of the survey were also used in the model. These are used to take into account variation due to differences in recall period between the rounds. Other variables used are as follows. A significant number of observations in Round 1 did not have information on employment status of household heads. So a dummy variable is included to capture those observations for which employment status is missing. A dummy variable taking value 1 if the observation belongs to older cohort of Round 1 is used to take into account the difference in recall periods for the younger and older cohorts in that round. Refer Section 5 for details.

It is possible that households that faced welfare loss from weather shocks or other income shocks are more vulnerable to health shocks. But this could not be controlled for in the analysis since *Young Lives* survey does not have information on chronological order of the shocks faced by households. Since weather related shocks affect many households in a particular area, this is captured to some extent by cluster-level intercepts and dummy for area of residence (urban/rural).

[12] Coping strategies like taking more work or reducing expenditure are mostly adopted by the poorest wealth quartile groups. The former involves household members working overtime or sending children to work while the latter involves reducing food or education expenditure of the household. These strategies have implications for human capital formation and hence are termed more costly than other strategies.

members of the same household, dummy variables indicating whether father or mother of the *Younglives* child was affected by ill-health are used. The base category is health shock faced by other members of the household. We hypothesise that more resources are allocated for treatment of an individual member whose contribution to household production is higher. Thus, we expect that households adopt very costly strategies when the father of *Younglives* child faces health shock as he is the breadwinner in a majority of the surveyed households. The household level characteristics used in the model include age, gender, education level and employment status of the head. Age of the household head is used as a proxy for life-cycle stage of the household and is likely to influence the coping strategies used. Sauerborn *et. al.* (1996) argued that as household matures, dependency ratios become more favourable and children move from being net consumers to net producers. Thus with increasing age households are more likely to rely on their savings to cope with health shocks. Regular salaried employment and high education levels are expected to reduce the adoption of costlier strategies like reducing consumption, borrowing and sale of assets. Indicators of socio-economic characteristics of the household like caste and religious groups and wealth quartile group are also used in the model. A dummy variable for RAS insurance coverage is used. Since all the transactions under the scheme are cashless, it also expected to reduce the incidence of borrowing, sale of assets etc. among the insured households which face health shocks.

Findings

It is important to establish if three-level model is required in the case of longitudinal and clustered data structure, i.e., if households' responses over time are significantly correlated with each other and if households nested in a geographical area are more alike. For this, we estimate the unconstrained or null model (i.e., model without the covariates $\boldsymbol{x_{ijk}}, \boldsymbol{x'_{jk}}, \boldsymbol{x''_{k}}$ in Equation 3) and test if the random effects are statistically significant at the household level and cluster level (h_{jk} and c_k

respectively). Table 3 shows the results of null model for health shocks as well as coping strategies. The null hypothesis that variances of h_{jk} and c_k are zero is rejected at 1 percent significance level in the case of health shocks as well as coping strategies. Thus, contextual factors play a significant role in determining the economic vulnerability to health shocks faced by households and coping strategies adopted by them[13].

Table 3: Results of Multi-Level Analysis – Null Model

Variable		Constant	se	σ_h^2	se	σ_c^2	Se
Health shock		-1.335***	0.226	0.159***	0.021	0.407***	0.192
Coping Strategy	Transfers	1.929***	0.447	3.143***	0.767	0.710***	0.213
	Credit /assets sale	2.285***	0.361				
	Work more	0.885**	0.350				
	Spend less	0.292	0.518				
	Others	1.464***	0.456				

Note: Robust standard errors are reported in parentheses (clustered for region); *** p<0.01, ** p<0.05.

The proportion of variance at the cluster level (correlation across households within the same cluster) is obtained using the following estimator: $\rho = \frac{\sigma_c^2}{\sigma_c^2+\sigma_h^2+\frac{\pi^2}{3}}$ where $\pi^2/3$ is the variance of ε_{ijk}. This is a high 10.6 percent for health shocks faced by households and 9.94 percent in the case of coping strategies. Thus, the results prove that cluster effects are highly significant.[14]

Economic Vulnerability to Health Shocks

This section details on the determinants of economic vulnerability to health shocks faced by households (Table 4). The base scenario refers to

[13] Around 4 percent of the households in Round 2 lived in a cluster different from that in Round 1 and this was 5 percent in the case of Round 3. However, a majority of the households migrated to a new cluster within the same region (Rayalaseema, Telengana, Coastal Andhra) and also the migration was mostly rural to rural or urban to urban. Such households (rural-rural and urban-urban migration within the same region) were assigned to their original cluster of Round 1 since we expect the community conditions to be similar. Other households were dropped from the sample.

[14] We also conduct LR tests of three-level versus two-level model and three-level versus single level model and obtain similar results.

no health shock reported by the household. The results of both pooled model as well as three level random intercept logit model are presented for comparison. The inclusion of random effects moderates the strength of the relation between the dependent variable and covariates (though the direction of relation remains the same for all the covariates). Also, the proportions of variance explained at the household level and cluster level decrease (in comparison with the null model) once the covariates are added.

Vulnerability to health shocks increases with the age of the household head and female-headed households have higher probability of facing welfare loss from health shocks than the male-headed ones. Completion of primary education and regular salaried employment of the household head have negative effects on vulnerability to health shocks but only the latter is statistically significant. Households with elderly member, chronically ill or disabled members and high dependency ratios are more prone to welfare loss from health shocks. Households belonging to bottom wealth quartile groups face higher economic vulnerability to health shocks compared to the topmost quartile group. Similarly, SC and Muslim households have higher incidence of welfare loss from serious illness or death compared to other caste and religious groups respectively. Also, households living in rural areas of Andhra Pradesh are more susceptible to reduction in well-being from health shocks compared to those in urban areas. Inclusion of households under Rajiv Arogyasri health insurance scheme does not have a significant effect in reducing the incidence of welfare loss from health shocks. Other studies like Mitchell *et. al*. (2011) and Selvaraj and Karan (2012) also found that the scheme did not have any clear effects on catastrophic medical spending.

Table 4: Factors Leading to Welfare Loss from Health Shocks (Rounds: 2002, 2006, 2009)

Variables	Complete Pooling		Random Effects (3 level)	
	Coefficient	Standard Error	Coefficient	Standard Error
Age	0.0230	0.015	0.0228***	0.006
Age squared	-0.0003	1.5e-4	-0.0003***	8.3e-5
Female	0.816***	0.098	0.820***	0.108
Education	-0.0635	0.068	-0.0665	0.046
Salaried	-0.0979	0.090	-0.110**	0.049
Disability	0.388***	0.084	0.395***	0.074
Elderly	0.477***	0.072	0.487***	0.102
Dependency ratio	0.0679	0.050	0.0679***	0.021
Quartile II	-0.0006	0.073	-0.0022	0.103
Quartile III	-0.130	0.080	-0.137	0.112
Quartile IV	-0.156	0.115	-0.160***	0.039
SC	0.113	0.075	0.133***	0.018
ST	0.0714	0.115	0.0763	0.200
Muslim	0.171	0.238	0.265***	0.088
Older cohort	0.162**	0.074	0.169**	0.067
Rural	0.861***	0.186	0.555***	0.156
Round 2	0.586***	0.084	0.593	0.402
Round 3	-0.042	0.147	-0.041	0.119
Old cohort of R1	0.368***	0.126	0.372***	0.070
Missing salaried	0.093	0.147	0.091	0.154
Insurance	-0.140	0.141	-0.147	0.176
Constant	-2.167***	0.362	-2.697***	0.343
Observations	8,751	-	8,751	-
Level 2 units	-	-	3,019	-
Variance at level2	-	-	0.096***	0.028
Level 3 units	-	-	20	-
Variance at level3	-	-	0.299***	0.168

Note: Dummy variables for clusters were included for the complete pooling model; standard errors reported take into account clustering at the region level for the three-level model.

The key variable of interest- coverage under state health insurance scheme has no significant effect on the likelihood of adopting costly coping strategies. The model specified might suffer from the problem of endogeneity if there is self-selection into the scheme (Wagstaff and Lindelow, 2008). But in the case of RAS, there is no separate enrolment for the scheme; all households that have BPL cards (by satisfying the income criteria of the state government) are automatically eligible for the insurance[15] and hence issue of self-selection may not arise in our context.[16]

Coping Strategies

This section details on factors affecting the likelihood of households adopting different coping strategies against health shocks using three-level multinomial logistic regression analysis (Table 5). Only those households that reported health shock are included in the analysis. The reference scenario pertains to households using savings as the first response. The characteristics of households adopting different coping strategies are as follows:

Savings: Households with middle-aged heads dissave to cope with economic costs of health shocks, but those with very elderly heads are more likely to resort to borrowing, transfers, reducing expenditure on consumption, taking more work etc. Households belonging to top wealth

[15] Source: http://www.aarogyasri.gov.in/ASRI/index.jsp accessed on 16th September, 2013

[16] However, if selection into the scheme is based on unobservables, the insurance and random intercepts are likely to correlated with one another and this will bias the coefficient on insurance (Wagstaff and Lindelow, 2008). One method to address the issue of endogeneity is through fixed effects (FE) model. But, estimation of FE model drops 50 percent of the observations in our sample due to no variation in dependent variable across time which in turn introduces sample bias. Hence, we check for the issue of self-selection in the following way. During Round 2 survey, 84.9 percent of the households possessed BPL cards (before the scheme was launched) and this increased to 90.6 percent in Round 3 survey (after the launch of the scheme in 2007). We introduce a dummy variable for those households that joined the BPL category after Round 2 assuming that they self-selected into the scheme. We then interact this dummy with the insurance variable to check if there is any selection bias. But the coefficient on the interaction term is not significant and coefficient on insurance is also not affected.

quartile groups are more likely to use savings compared to other strategies to manage the economic costs of health shocks.

Increase Work or Reduce Consumption: Households that face serious illness or death of father of the *Younglives* child are more likely to adopt strategies like reducing consumption and children or other members of family taking work. This might be due to the fact that father of the *Younglives* child is the breadwinner in a majority of the sample households. Since, health shock to the earning member results in high indirect costs in addition to the direct costs, the household resorts to very costly coping strategies. SC and female headed households are more likely to send children or other members to work to manage the costs of health shocks while those with heads who have completed primary education or have regular salaried employment are less likely to opt for such a strategy. Regular salaried employment also reduces the likelihood of cutting down expenditure on food, education etc. while Muslim households are more likely to adopt this strategy in comparison with other socio-economic groups. The coefficients on rural areas have signs contrary to the expected results as they imply that these households are less likely to use costly strategies compared to their urban counterparts.

Credit or Sale of Assets: This strategy is more commonly used among SC and Muslim households. Also, households belonging to top wealth quartile groups are least likely to borrow from formal or informal sources and sell assets. The key variable of interest- coverage under state health insurance scheme did not have any effect on the likelihood of adopting costly strategies to cope with health shocks.

Table 5: Coping Strategy Used by Households (Rounds: 2006, 2009)

Variables	Receive Help	Credit or Sale of Assets	Take More Work	Reduce Expenditure	Others
Father	0.535	0.531	0.485***	0.934***	-0.362
	(0.366)	(0.433)	(0.0611)	(0.228)	(0.283)
Mother	0.221	0.166	-0.299	0.317	-0.776***
	(0.463)	(0.541)	(0.375)	(0.313)	(0.216)
Head age	-0.230***	-0.215***	-0.266***	-0.207**	-0.257***
	(0.044)	(0.043)	(0.034)	(0.083)	(0.057)
Age squared	0.002***	0.002***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.737	0.0541	1.076***	0.896	0.722
	(0.752)	(0.527)	(0.401)	(0.951)	(0.706)
Education	-0.098	-0.079	-0.224***	0.302	-0.050
	(0.564)	(0.184)	(0.049)	(0.572)	(0.548)
Regular salaried	-0.696***	-0.360	-0.966***	-1.246***	-0.385
	(0.157)	(0.353)	(0.217)	(0.444)	(0.266)
Quartile II	-0.585***	-0.789***	-0.609***	-0.852	-0.906***
	(0.114)	(0.259)	(0.074)	(0.658)	(0.132)
Quartile III	-0.794	-1.009***	-0.938***	-1.828***	-0.761***
	(0.539)	(0.343)	(0.255)	(0.038)	(0.247)
Quartile IV	-1.609**	-2.026***	-2.232***	-2.184***	-1.408***
	(0.672)	(0.520)	(0.098)	(0.139)	(0.432)
SC	0.250	0.300***	0.802***	0.389	0.582
	(0.250)	(0.108)	(0.270)	(0.227)	(0.350)
ST	0.136	-0.177*	0.307	0.555	0.212
	(0.669)	(0.098)	(0.319)	(0.736)	(0.516)
Muslim	0.680***	0.485***	0.818	0.996***	0.785***
	(0.219)	(0.120)	(0.785)	(0.141)	(0.248)
Dependency	0.148	0.138	0.222	-0.277	0.250
	(0.222)	(0.117)	(0.174)	(0.402)	(0.198)
RAS card	0.453	0.118	0.031	-0.376	0.089
	(0.239)	(0.258)	(0.227)	(0.555)	(0.358)
Old cohort	0.404	0.490	0.771	0.759	0.405
	(0.286)	(0.335)	(0.474)	(0.432)	(0.443)
Rural	-1.356	-0.688	-1.103***	-1.816***	-1.386
	(0.737)	(0.538)	(0.419)	(0.254)	(0.750)
Round 3	-1.026**	-0.736	-0.672	-0.678	-1.111
	(0.399)	(0.437)	(0.624)	(1.309)	(0.679)
Constant	8.705***	8.338***	8.344***	7.746**	9.292***
	(0.447)	(0.521)	(0.479)	(3.282)	(1.949)
Number of level 1 units		1,659			
Number of level 2 units		1173	Variance at level 2		2.400 (.939)
Number of level 3 units		20	Variance at level 3		0.758 (.321)

Note: Robust standard errors are reported in parentheses (clustered for region).

Sum-up

It is important to know who are vulnerable to health shocks, what are the household responses to cope with economic burden of health shocks and if policy programs are effective in reducing this economic vulnerability. Vulnerability to welfare loss from health shocks is higher among households with elderly and disabled members and those with female heads. Similarly, poorest households and those in the rural areas are the worst affected by health shocks. The results show that regular salaried employment of the household head reduced the vulnerability to health shocks and the probability of using costly strategies like reduction of consumption expenditure and sending children or other members to work. Socially vulnerable groups like SC and Muslim households are more likely to use costly strategies to cope with health shocks which lead to higher welfare loss among these groups.

Rajiv Arogyasri health insurance scheme does not have a significant effect in reducing the household welfare loss from health shocks and their coping strategies. This is because only 3.76 percent of the eligible households accessed benefits under the scheme. There can be several reasons behind this. The insurance scheme covers mostly in-patient expenditures only. But out-patient services and costs of medicines contributed to 80 percent of OOP medical expenditures and hence the insurance scheme by design cannot eliminate catastrophic spending arising out of such cases (Fan *et. al.*, 2012; Shahrawat and Rao, 2012). Diseases like TB, Infectious diseases, Malaria, Filaria, Gastroenteritis and Jaundice are not covered under the insurance since they are already addressed under national health programmes. But these are still leading causes of serious ailments among the poor (Reddy and Mary, 2013). Thus, the scheme is skewed towards high-cost medical interventions which account for less than two percent of the disease burden of the population (Prasad and Raghavendra, 2012). Added to this, the utilization rates (number of treatments preauthorized per lakh of the beneficiaries covered) under the scheme are highest in those districts with good

access to hospitals. Thus, more than 90 percent of preauthorized surgeries were performed in cities with a good network of hospitals while the districts with poor health infrastructure accounted for less than 10 percent (Prasad and Raghavendra, 2012). This indicates that contextual factors like physical proximity to hospitals are important determinants of households seeking medical care under the insurance scheme. In addition to this, the utilization rates for disadvantaged groups like SC and ST were lower than their population proportions (Fan *et. al*., 2011; Rao *et. al*. 2012). Besides, it might be little early or premature to evaluate the effect of the state insurance scheme since it was launched only in 2007 and the government was in the process of expanding the scheme by including more procedures and diseases under insurance coverage.

The conclusions of the study have certain caveats attached to them. The dataset may not be representative sample of households in Andhra Pradesh as only those with one-year or eight-year old children were included for the panel survey in 2002. The study uses self-reported measures of health shocks as the dependent variable which has its own limitations. Perceptions of reduction in economic well-being due to health shocks might vary across households. One cannot know if the welfare loss is predominantly due to direct costs or indirect costs of health shocks. If indirect costs contribute significantly to the economic burden, public health insurance schemes cannot prevent the reduction in well-being arising out of these costs. Nevertheless, the study complements the existing literature by identifying factors causing economic vulnerability to health shocks and their coping strategies. This helps in better targeting of public health insurance schemes of the central and state governments. The importance of contextual factors like access to medical care suggests that protection through social insurance schemes should go hand in hand with the improvement of public health systems.

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APPENDIX

Table I: Differences in Questionnaires of Three Survey Rounds

	Round 1	Round 2	Round 3
Health shocks	Since your pregnancy with the *Younglives* child, has there been a major event that decreased the economic welfare of the household? - Severe illness or injury - Death or reduction in household members	Have there been following events within the family that have affected the household economy negatively since the last time we came to see you? -Death of child's father -Death of child's mother -Death of another person from the household -Serious illness of child's father - Serious illness of child's mother - Serious illness of another person from the household	Have there been following events within the family that have affected the household economy negatively since the last time we came to see you? -Death of child's father -Death of child's mother -Death of another person from the household -Serious illness of child's father - Serious illness of child's mother

(Contd …Table I)

(Contd …Table I)

	Round 1	Round 2	Round 3
Coping strategies	Which were the three worst events? What was the household response to the worst event?	What did your household do in response to these events? -Death of child's father -Death of child's mother -Death of another person from the household -Serious illness of child's father - Serious illness of child's mother - Serious illness of another person from the household	What did your household do in response to these events? -Death of child's father -Death of child's mother -Death of another person from the household -Serious illness of child's father - Serious illness of child's mother

Table II: Definition of Variables

Variable	Definition
Dependent Variables	
Health shock 0- No health shock 1- Faced health shock	None of the members faced serious illness/death One or more household members faced serious illness or death that reduced the economic well-being of the household
Coping strategies 1- Used savings 2- Transfers 3- Borrowed/sold assets 4- Worked more 5- Reduced expenditure 6- Others	The first response of the household when it faced health shock Used savings Received help from relatives, NGOs, government, friends, neighbours, community etc Borrowed from formal or informal sources, mortgaged assets, sold belongings/possessions/animals/properties Sent children to work, started work, worked more, migrated to find work Ate less, bought less, took children out of school, sent children to be cared for by friends Nothing, fled or moved away, others
Member	
Father	Father of the *Younglives* child faced serious illness or death
Mother	Mother of the *Younglives* child faced serious illness or death
Other member	Other members of the household faced serious illness or death
Head characteristics	
Age	Age of the head of the household
Age squared	Squared age of the head

(Contd …Table II)

Variable	Definition
Female	Dummy takes value 1 if the sex of the household head is female
Education	Dummy variables takes value 1 if the head has completed primary education
Salaried	Dummy for household head has a regular salaried job
Demographic characteristics	
Disability	Dummy variable takes values 1 if one or more household members are disabled
Elderly	Dummy variable takes value 1 if there are one or more household members above 60 years of age
Dependency ratio	(Number of household members aged 0-14 and >64) / Number of households members aged 15-64
Socio-economic characteristics	
Wealth index Quartile I Quartile II Quartile III Quartile IV	Wealth index is constructed as a sum of housing quality index, consumer durables index and services index (Young lives report). Quartile I takes value 1 if the household belongs to the bottom 25 percent and Quartile IV takes value 1 if the household belongs to the top 25 percent wealth group.
SC	Dummy variables takes value 1 if the household belongs to SC category
ST	Dummy variables takes value 1 if the household belongs to ST category
Muslim	Dummy variable takes value 1 if it is a Muslim household
Insurance	Dummy variable take value 1 if the household is covered by public health insurance scheme (Rajiv Arogyasri) in Round 3. The variable takes value 0 in the case of Round 1 and Round 2.

Variable	Definition
Community Characteristics	
Rural	Dummy variable takes value 1 if the household lives in rural area
Clusters (1-20)	Dummy variable takes value 1 if the household belongs to that cluster (Taluk)
Others	
Round 2	Dummy for second round of survey – 2006
Round 3	Dummy for third round of survey – 2009
Older cohort	Dummy take value 1 if the household belongs to the older cohort
Older cohort of R1	Dummy takes value 1 for older cohort households in Round 1
Missing salaried	Dummy takes value 1 if data is missing for regular salaried variable (Some observations in Round 1 had data missing on regular salaried employment)

Table III: Summary Statistics

Variables	Younger Cohort			Older Cohort		
	R1	R2	R3	R1	R2	R3
Observations	2,011	1,950	1,930	1,008	994	975
Attrition rate (from R1)	-	3.03	4.03	-	1.39	3.27
Head						
Age (Mean years)	39.96	38.51	38.58	40.17	42.51	44.16
Female	8.45	5.18	5.44	7.84	10.87	11.20
Education	41.22	38.21	40.57	40.18	35.11	34.97
Regular salaried	14.47	14.92	16.89	16.27	14.48	16.51
Dependency						
Elderly	11.88	19.85	38.81	11.31	18.51	32.72
Disabled	13.87	9.03	9.74	11.01	9.36	7.59
Dependents ratio (Mean)	0.69	0.93	1.05	1.12	0.84	0.44
Religion						
Hindu	90.95	91.69	91.87	92.06	92.15	92.21
Muslim	7.76	7.33	7.20	6.65	6.54	6.46
Christian	1.19	0.92	0.88	1.29	1.31	1.33
Caste						
SC	18.20	18.15	18.08	20.34	20.42	20.31
ST	12.73	12.82	12.85	10.12	10.06	10.05
OBC	47.39	47.95	48.13	48.71	48.79	48.92
OC	21.68	21.08	20.93	20.83	20.72	20.72
Residence						
Rural	74.89	75.33	75.28	75.10	75.35	75.49
Urban	25.11	24.67	24.72	24.90	24.65	24.51
Region						
Coastal	34.81	35.09	35.18	34.72	34.51	34.56
Rayalaseema	30.13	29.91	29.89	30.46	30.48	30.05
Telangana	35.06	34.99	34.92	34.82	35.01	35.38
RAS card (Insurance coverage)	-	-	82.64	-	-	84.82

Note: All numbers are in percent ages except mentioned otherwise.

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