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for rural south India**

by

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**Vulnerability and Poverty in Rural India-Estimates for Rural South
India**

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Abstract

An attempt is made to assess the vulnerability of rural households in the semi-arid tract of South India, based upon the ICRISAT panel survey. We employ both *ex ante* and *ex post* measures of vulnerability. The latter are decomposed into aggregate and idiosyncratic risk, and poverty components. Our decomposition shows that idiosyncratic risks account for the largest share (37%), followed by poverty (35%) and aggregate risks (22%). It is somewhat surprising that idiosyncratic risks (e.g. illness or unemployment) contribute more than poverty. Despite some degree of risk-sharing at the village level, the landless or small farmers are vulnerable to idiosyncratic risks, forcing them to reduce consumption. Subsets comprising the landless without education or members of lower castes are most vulnerable. Income augmenting policies must therefore be combined with those that not only reduce aggregate and idiosyncratic risks but also build resilience against them.

Key words: aggregate and idiosyncratic risks, poverty, vulnerability, decomposition, resilience, panel data analysis.

JEL codes: C21, C23, C61, I32

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Vulnerability and Poverty in Rural India-Estimates for Rural South India²

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I. Introduction

The objective of this study is to assess the vulnerability of rural households in the semi-arid region of South India to aggregate and idiosyncratic risks (crop and weather risks, and illness and unemployment risks, respectively). Vulnerability is distinguishable from “poverty”³ in the sense that there exist those who are non-poor but vulnerable, and those non-vulnerable but poor. However, as a measure of deprivation, vulnerability is more appealing as it takes into account not just fluctuating levels of living but also the resilience of subsets of households (e.g. landless, smallholders) against aggregate and idiosyncratic shocks. It is, however, more difficult to identify the vulnerable not only because there are different measures (e.g. *ex ante* versus *ex post* vulnerability) but also because tracking the well-being of a particular household over many years or before and after a shock requires reliable panel data that are seldom available.

There has been a surge of interest in measuring vulnerability. Important contributions include Hoddinott and Quisumbing (2003a b), Ligon and Schechter 2003, 2005), Gaiha and Imai (2004) and Dercon (2005). So one objective of the present study is to review different measures of vulnerability and apply them to the panel data for semi-arid rural South India

These studies also point to the need for designing anti-poverty policies to address vulnerability-especially in rural areas where agricultural yields and revenues fluctuate a great deal due to changes in weather, floods, pest infestation, and market forces. Besides, different segments of rural population are exposed to idiosyncratic risks in the absence of easy access to medical care, drinking water, unhygienic living conditions, and limited opportunities for diversifying income sources. These difficulties are compounded by lack of financial intermediation and formal insurance, credit market imperfections, and weak infrastructure (e.g. physical isolation because of limited transportation facilities). More specifically, if the policy makers design poverty alleviation policies in the current year on the basis of a poverty threshold of income in the previous year, “the poor” who receive income support may have already escaped from poverty and “the non- poor” who do not may have slipped into

² This study was sponsored by IFAD. We are grateful to T. Elhaut and to G. Thapa, for their support, encouragement and advice. The views expressed here, however, are our own, and not necessarily of IFAD.

³ See, for example, Gaiha and Thapa (2005), Hoddinott and Quisumbing (2003a b), and World Bank (2000).

poverty due to various unanticipated shocks (e.g. changes in relative crop prices). One approach would be to focus on poverty dynamics (e.g. Gaiha and Deolalikar, 1993, Baulch and Hodinott, 2000) or chronic poverty (e.g. Hulme, Moore and Shepherd, 2001), taking into account poverty transition or the long-term poverty status *ex-post*. Another, and, a more challenging, approach would be to combine both *ex ante* and *ex post* measures of vulnerability. This, however, presupposes that many of the risks- both aggregate and idiosyncratic- and resilience of subsets of households against such shocks can be anticipated. This is easier said than done. It is nevertheless arguable that, to the extent that *ex post* measures can be combined with *ex ante* measures of vulnerability, it would help design a more effective strategy to deal with vulnerability.

As a case study, we will construct vulnerability measures of households in semi-arid rural India drawing upon the ICRISAT household data for 1975-84. While several recent studies analyse vulnerability using the ICRISAT data- a recent important contribution being Ligon (2005)- none of these employ the various measures proposed and focus on who the vulnerable are and whether they are distinguishable from the poor in a static sense.⁴ So our analysis is designed to be more comprehensive and richer from a policy perspective. The rest of the paper is organized as follows. In Section II, a review of salient features of the ICRISAT panel survey is followed by a discussion of measurement errors in the consumption expenditure data and their implications for insurance. Section III gives an exposition three different empirical methodologies used here to measure vulnerability of households. Econometric results and findings are summarized in Section IV. The final section offers concluding observations.

II. Data

(1) ICRISAT Data⁵

The analysis is based on (a sub-set) of the ICRISAT Village Level Studies (VLS) data sets that cover the semi-arid tract (SAT) in Maharashtra and Andhra Pradesh. Agroclimatologically, the SAT includes those tropical regions where rainfall exceeds potential evaporation four to six months in a year. Mean annual rainfall ranges from about 400 to 1,200 mm. India's SAT is vast and covers about 15 to 20 large regions, each embracing several districts. Based on cropping, soil and climatic criteria, three contrasting dryland agricultural regions were selected by ICRISAT: the Telengana region in Andhra Pradesh, the Bombay Deccan in Maharashtra, and the Vidarbha region also in Maharashtra. Three representative districts viz. Mahbubnagar in the Telengana region, Sholapur in the Bombay Deccan and Akola in the Vidarbha region

⁴ Examples include Rosenzweig and Wolpin's (1993), Chaudhuri and Paxson (1994), Townsend (1994), Ravallion and Chaudhuri (1997), Jacoby and Skoufias (1998), Lim and Townsend (1998) and Gaiha and Imai (2004). See the next section for more details.

⁵ This subsection draws upon Gaiha and Imai (2004).

were selected on rainfall, soil and cropping criteria. Next, typical talukas (i.e. smaller administrative units) within these districts were selected, followed by the selection of 6 representative villages within these talukas. Finally, a random stratified sample of 40 households was selected in each village. This comprised a sample of 30 cultivator and 10 landless labour households. To ensure equal representation of different farm size groups, the cultivating households were first divided into three strata, each having an equal number of households. A random sample of 10 households was drawn from each tercile. 10 landless labour households were also randomly selected. Landless labour households were defined as those operating less than half an acre (0.2 ha) and whose main source of income was agricultural wage earnings. All households were interviewed by investigators who resided in the sample villages, had a university degree in agricultural economics, came from rural backgrounds, and spoke the local language.

A fixed sample size of cultivator and landless labour households in each village means that the sampling fractions and relative farm sizes that demarcate the cultivator terciles vary from village to village. The likelihood that a village household was in the sample ranged from about one in four in the smaller Akola villages to about one in ten in the larger Mahbubnagar villages. Landless labour households are somewhat underrepresented in the sample. On average across the 6 villages, they comprise about one-third of the households in the household population of interest, but their share in the sample is only one-quarter. However, since their mean household size is less than that of cultivator households, a one-quarter representation is a fair reflection of their presence in the individual population of interest (Walker and Ryan, 1990).

The data collected are based on panel surveys carried out at regular intervals from 1975 to 1984 covering production, expenditure, time allocation, prices, wages, and socio-economic characteristics of 240 households in the sample villages representing 3 agro-climatic zones in the semi-arid region in South India. A description of the agro-climatic and other characteristics of the sample villages is given in Appendix 1. Given the agro-climatic conditions and purposive selection of the villages, the VLS data are not representative of all of rural south India or, for that matter, even of its semi-arid region. Nevertheless, the longitudinal nature and richness in terms of variables included are what make the ICRISAT VLS data unique.

The present analysis is based on data for 183 households belonging to 5 sample villages (excluding Kinkheda), as continuous data over the period 1975-84 are available on this subset of households. This sub sample is used to construct one measure of vulnerability i.e. vulnerability as expected poverty (VEP)⁶. However, given the debate on measurement errors in the consumption expenditure data, measures of vulnerability based on both consumption expenditure and income vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER, the use of the original ICRISAT data is problematic. We shall therefore use expenditure data provided by Gautam (1991) for three villages, viz. Aurepalle, Shirapur and Kanzara to derive estimates of VEU and VER measures.

⁶ An exposition of different measures of vulnerability is given in a subsequent section.

(2) Measurement Errors

Even though it is widely believed that the ICRISAT data are rich and reliable, they are, of course, not free from some measurement problems. Some doubts, for example, have been raised on consumption of home production and grain stocks. As these errors have implications for consumption smoothing, a brief review of important studies is given below.

Ravallion and Chaudhuri (1997) report a systematic underreporting of own consumption of crop outputs produced. Without an appropriate adjustment, Townsend (1994) overestimates the degree of risk sharing in the village. Gautam (1991) shows that the difference between *inflow* of crop inventory (*i.e.*, production calculated from agricultural production files) and its *outflow* (*i.e.*, crop sales *plus* consumption of own-produced crops from the transaction files) is much larger than the increase in grain stock derived from the annual stock files. He is emphatic that this discrepancy is due to the fact that only a part of consumption of home production is reported in the transaction files. However, based on their investigation of the data, Jacoby and Skoufias (1993) argue that 'ICRISAT's methodology captures at least part, if not the majority, of consumption out of home production.' (p.8), as (1) grains which were brought to commercial millers⁷ were systematically recorded, and (2) the proportion of consumption of own-produced grain stocks in total grain stocks (26 to 37 percent) is not particularly low. They therefore conclude that both production and stocks data are suspect (since consumption of home production is more or less accurate). Thus it is difficult to be sure of the reasons for the discrepancy. So we shall use the (adjusted) expenditure data provided by Gautam (1991), and Ravallion and Chaudhuri (1997), as these are arguably the most plausible.⁸

(3) Risks and Insurance

Jacoby and Skoufias (1998) estimate the household response to anticipated and unanticipated income changes, using the ICRISAT data. In their analysis, if the permanent income hypothesis holds, the consumption change is affected positively by unanticipated income changes and not by anticipated income changes. Using the data for Aurepalle and Kanzara, their analysis does not reject the permanent income hypothesis.

Rosenzweig and Wolpin's (1993) focus on the role of bullocks as buffer stock for consumption by credit-constrained households in rural India. They find that sales of bullocks increase when incomes are low, and purchases increase when incomes are high. On the other hand, Lim and Townsend (1998), through a detailed investigation

⁷ Jacoby and Skoufias (1998) show that most of the households rely on commercial milling as it is more economical than own-milling at home.

⁸ Note that the correlation coefficient of original consumption data and Gautam's data we use is only 0.41 which suggests a considerable discrepancy between the two.

of how rural farming households financed their monthly deficit, reach the conclusion that livestock including bullocks and other capital assets play little part in smoothing inter-temporal shocks. Instead, buffer stock of crop inventory and currency, together with credit or insurance, are much more important. Chaudhuri and Paxson (1994), also using the monthly ICRISAT data, investigate the impact of seasonality on income and consumption. They conclude that seasonal patterns in consumption are common across households within villages but are unrelated to income seasonality.

On risk-sharing, Townsend (1994) tests the perfect risk-sharing hypothesis that household consumption is fully insured against idiosyncratic shocks and thus depends only on the aggregate risk. Although this hypothesis is rejected, he shows that the model provides a surprisingly good benchmark in that household consumption comoves with average village consumption, implying risk-sharing among households. Ravallion and Chaudhuri (1997) point to a weaker result, if an allowance is made for measurement errors in own consumption and alternative specifications and estimation procedures are considered. They also draw attention to the possibility that common signals about future income, rather than consumption insurance, would generate comovements in consumption, under the permanent income hypothesis. Lim and Townsend (1998), however, disagree on the grounds that there is non-negligible social interaction among households, as credit/ insurance/ gift account for a large part of the difference between expenditure and revenue.

Responses to aggregate and idiosyncratic risks take other forms too. Changes in child school attendance (Jacoby and Skoufias, 1997) and in labour hours in off-farm market (Kochar, 1995, 1999), for example, have been reported. Scandizzo, Gaiha, and Imai (2004, 2005) and Imai (2003), on the other hand, focus on the role of the Maharashtra Employment Guarantee Scheme (EGS) in coping with risk and seasonality of income. While Scandizzo, Gaiha, and Imai (2004) confirm that the EGS helped stabilise incomes during lean periods, in a companion piece Scandizzo, Gaiha, and Imai (2005) also report that in an uncertain labour market environment relatively affluent labour households are likely to participate more in the EGS, given its higher option value for them. Thus the poor labourers are likely to be at a disadvantage.

Another recent study by Gaiha and Imai (2004) examines the vulnerability of rural households to poverty when a negative crop shock occurs, using a dynamic panel data model that takes into account effects of crop shocks of varying intensity and duration. They show that even sections of relatively affluent households are highly vulnerable to long spells of poverty when severe crop shocks occur in consecutive years.

Although conclusions differ depending on the questions asked and methodologies used, some of the major findings are summarised below.

- Both poor and relatively affluent households are vulnerable to aggregate shocks such as crop shocks.
- The ability to cope with shocks is generally limited due to limited consumption insurance or risk sharing, and credit constraints.

- Risk-coping ability is likely to differ among households because of differences in assets, such as livestock, crop inventory and currency. As a result, the poor (mostly assetless) are more likely to increase child or adult labour hours.
- Existing policy interventions such as the Employment Guarantee Scheme, do not necessarily reach the poor despite their potential risk-reducing roles. So there is a case for more effective risk reducing, mitigating and coping interventions alongside income augmenting policies.

III. Methodology

Hoddinott and Quisumbing (2003a, b) provide a comprehensive review of recent approaches and a “toolkit” to quantify vulnerability of households and data requirements. We will use the following three approaches identified by them (Hoddinott and Quisumbing, 2003 b)⁹.

(1) Vulnerability as Expected Poverty (VEP)

VEP is an *ex ante* vulnerability measure, proposed by Chaudhuri, Jalan and Suryahadi (2002) who applied it to the Indonesian household data.

Consider first an example of VEP. This is the case of vulnerability defined as the probability that a household will fall into poverty in the future.

$$V_{it} = \Pr (c_{i, t+1} < z) \quad (1)$$

where vulnerability of household at time t , V_{it} , is the probability that the i -th household’s level of consumption at time $t+1$, c_{it+1} , will be below the poverty line, z .¹⁰

In a variant that allows for the degree of vulnerability to rise with the length of the time horizon, vulnerability of household h for n periods, denoted as $R(\cdot)$ for risk, is the probability of observing at least one spell of poverty for n periods, which as shown below is one minus the probability of no episodes of poverty:

$$R_i(n, z) = 1 - [(1 - (P(c_{i, t+1}) < z)) \dots (1 - P(c_{i, t+n}) < z))] \quad (2)$$

Following this definition and using $I(\cdot)$ as an indicator equalling 1 if the condition is true and zero otherwise, an alternative measure of vulnerability is that a household is vulnerable if the risk in n periods is greater than a threshold probability, p ¹¹.

⁹ For a more detailed exposition, see Gaiha and Thapa (2006).

¹⁰ The poverty cut-off point we use represents the minimum cost of a nutritionally adequate diet i.e. Rs 180 per capita per year (at 1960-61 prices), which has been widely used in the literature (see Gaiha and Imai, 2004, for more details).

¹¹ See, for example, Pritchett et al. (2000).

$$V_i(p,n,z) = I \{ R_{it} (n,z) > p \} \dots\dots\dots(3)$$

Neither (1) nor (3) takes into account other dimensions of poverty (e.g. depth of poverty). This limitation is easily overcome by rewriting equation (1) as

$$V_{it} = \sum^S p_s \cdot P(c_{i,t+1}, z) = \sum^S p_s \cdot I [c_{i,t+1} = z] \cdot [(z - c_{i,t+1}) / z]^\alpha \quad (1')$$

where $\sum^S p_s$ is the sum of the probability of all possible 'states of the world', s in period $t+1$, and α is the welfare weight attached to the gap between the benchmark and the welfare measure (as in the Foster-Greer-Thorbecke poverty measure (1984)). In principle, this welfare weight could take values 0,1, 2.¹² Aggregating across N households¹³,

$$VEP_t = (1/N) \sum^N_i \sum^S p_s \cdot I [c_{i,t+1} = z] \cdot [(z - c_{i,t+1}) / z]^\alpha \quad (4)$$

A vulnerability measure such as (4) has considerable relevance. In Indonesia, for example, the headcount index of poverty was low before the financial crisis but rose sharply in its wake. This implies that a large proportion of those above the poverty line were vulnerable to shocks. There are two risks in such a context. If the headcount index is low, governments/donors might become complacent. If negative shocks are frequent and severe, such complacency would be misplaced. Besides, if the characteristics of those above the poverty line but vulnerable to shocks differ from those of the poor, targeting the latter may miss a significant proportion of those whose living standards may decline sharply when a shock occurs.

Empirically, a variant of VEP is derived by the following procedure, as in Chaudhuri, Jalan and Suryahadi (2002). The consumption function is estimated as:

$$\ln c_i = X_i \beta + e_i, \quad (5)$$

where c_i is per capita consumption expenditure for the i -th household, X_i represents a bundle of observable household characteristics, β is a vector of parameters of aggregates shocks, and e_i is a mean-zero disturbance term that captures idiosyncratic shocks that contribute to different per capita consumption levels. It is assumed that the structure of the economy is relatively stable over time and hence, future consumption stems solely from the uncertainty about the idiosyncratic shocks, e_i . It is also assumed that the variance of the disturbance term depends on:

¹² These three values of α represent the headcount, depth of poverty and distributionally sensitive measures of poverty in the Foster-Greer-Thorbecke class of poverty indices.

¹³ In a related measure, Kamanou and Morduch (2002) define vulnerability as expected change in poverty, as opposed to expected poverty *per se*. Specifically, they define vulnerability in a population as the difference between the expected value of a poverty measure in the future and its current value.

$$\sigma_{e,i}^2 = X_i \theta \quad (6)$$

The estimates of β and θ could be obtained using a three-step feasible generalized least squares (FGLS). Using the estimates $\hat{\beta}$ and $\hat{\theta}$, we can compute the expected log consumption and the variance of log consumption for each household as follows.

$$\hat{E}[\ln C_i | X_i] = X_i \hat{\beta} \quad (7)$$

$$\hat{V}[\ln C_i | X_i] = X_i \hat{\theta} \quad (8)$$

By assuming $\ln c_t$ as normally distributed, the estimated probability that a household will be poor in the future (say, at time $t+1$), is given by:

$$\hat{v}_i = \hat{P}r(\ln c_i < \ln z | X_i) = \Phi \left(\frac{\ln z - X_i \hat{\beta}}{\sqrt{X_i \hat{\theta}}} \right) \quad (9)$$

This is an *ex ante* vulnerability measure that can be estimated by cross-sectional data. Equation (9) will provide the probability of a household at time t becoming poor at $t+1$ given the distribution of consumption at t .

A merit of this vulnerability measure is that it can be estimated only by cross-sectional data. However, the measure correctly reflects a household's vulnerability only if the distribution of consumption across households given the household characteristics at one time represents the time-series variation of consumption of the household. Hence this measure requires a large sample in which some households experience good time and others suffer from negative shocks. Also, the measure is unlikely to reflect *unexpected* large negative shocks e.g Asian financial crisis, if we use the cross-section data for a normal year.

The sample size of the ICRISAT data is of course not large enough for estimating VEP measures. So we have included all households in five sample villages. Also, to make our results comparable with some earlier studies (e.g. Gaiha and Deolalikar, 1993; Gaiha and Imai, 2004), we replace log consumption with log income per capita in the above specification. The VEP simply assumes that consumption vulnerability derives from the stochastic property of the inter-temporal consumption stream it faces (Chaudhuri, Jalan and Suryahadi, 2002). Since the time-series variation of log income per capita with particular household characteristics can be approximated by the cross-sectional variation of the households with similar characteristics, consumption in the above specification can be replaced by income. Also, nothing precludes us from extending it to the panel data. So we will use both annual cross-section components and panel data in the ICRISAT data to construct VEP measures.

Our specification of VEP can be written as follows, based on two earlier studies

(Gaiha and Deolalikar, 1993; Gaiha and Imai, 2004).

$$\ln Y_i = X_i' \beta_1 + L_i' \beta_2 + H_i' \beta_3 + e_i \quad (10)$$

$$\sigma^2_{e,i} = X_i' \theta_1 + L_i' \theta_2 + H_i' \theta_3 \quad (11)$$

where i indexes the household. Y_i is per capita annual household income from all sources (in constant prices) in a particular crop year. X_i is a vector of household characteristics (e.g. age of household head and its square, household size and its square, and caste). L_i is a vector of owned land area and its square, the share of irrigated land in the total, and non-land assets (i.e. production assets) and its square. H_i is a vector of human capital, such as schooling years of household head. $\sigma^2_{e,i}$ is the variance of the disturbance term which is affected by various household characteristics. This can be estimated by a three-step feasible generalized least squares (FGLS).¹⁴

(2) Vulnerability as Expected Low Utility (VEU)

There is a problematic or perverse feature of VEP. In case $\alpha > 1$, the FGT poverty index attributes risk-aversion to households. Consider two scenarios. In the first, the risk-averse household is certain that expected consumption in period $t+1$ will be just below the poverty line so that the probability of poverty (or vulnerability) is one. In the second scenario, while expected mean consumption is unchanged, there is a 0.5 probability that this household's consumption will be just above the poverty line (and above the mean) and a 0.5 probability that the consumption will be just below the mean. Since the household is risk averse, it would prefer the certain consumption in the first scenario to the expected in the second but the vulnerability is lower in the second (it drops from 1 to 0.5). An implication for policy makers is to introduce new risks or remove insurance. Moreover, even when $\alpha > 1$, the FGT index implies increasing absolute risk aversion, contrary to empirical evidence. This weakness is sought to be overcome by Ligon and Schechter (2003). A brief exposition of this measure is given below.

In this measure of VEU, vulnerability is defined as the difference between the utility derived from some level of certainty-equivalent consumption, z_{ce} , at and above which the household is not considered vulnerable, and the expected utility of consumption. In other words, this certainty-equivalent consumption is akin to a poverty line. Consumption of a household, c_i , has a distribution in different states of the world, so this measure takes the form:

$$V_i = U_h(z_{ce}) - EU_i(c_i) \quad (12)$$

¹⁴ See Chaudhuri, Jalan and Suryahadi (2002) and Hoddinott and Quisumbing (2003b) for technical details.

where U_h is a (weakly) concave, strictly increasing function. Equation (12) can be rewritten as

$$V_i = [U_i(z_{ce}) - U_i(Ec_i)] + [U_i(Ec_i) - EU_i(c_i)] \quad (13)$$

The first bracketed term on the right is a measure of poverty in terms of the difference in utility between z and c . The second term measures the risk that household h faces. The latter can be decomposed into aggregate or covariate and idiosyncratic risk, as shown below.

$$\begin{aligned} V_i = & [U_i(z_{ce}) - U_i(Ec_i)] && \text{(Poverty)} \\ & + \{U_i(Ec_i) - EU_i[E(c_i|\bar{x})]\} && \text{(Covariate or Aggregate Risk)} \\ & + \{EU_i[E(c_i|\bar{x})] - EU_i(c_i)\} && \text{(Idiosyncratic Risk)} \end{aligned} \quad (14)$$

Aggregating across households, an estimate of aggregate vulnerability is obtained:

$$VEU = (1/N) \sum_i \{ [U_i(z_{ce}) - U_i(Ec_i)] + \{U_i(Ec_i) - EU_i[E(c_i|x_t)]\} + \{EU_i[E(c_i|x_t)] - EU_i(c_i)\} \} \quad (15)$$

This decomposition is useful as it allows an assessment of whether vulnerability is largely a result of factors underlying poverty (e.g. low assets and/or low returns from them) or of aggregate and idiosyncratic shocks and the inability to cope with them. However, two limitations must be noted. One is that the results may differ depending on the form of the utility function assumed¹⁵. The second is that the measurement is in terms of utility (i.e. utils).

Ligon and Schechter (2003) assumes a particular form of consumption function,

$$U'(c) = \frac{c^{1-\gamma}}{1-\gamma} \quad (16)$$

where γ denotes household's sensitivity to risk and inequality. They set $\gamma = 2$ following the microeconomic literature. We have set $\gamma = 2$ in the present study. They assume:

$$E(c_{it} | \bar{X}_t, X_{it}) = \alpha_i + \eta_t + X_{it}\beta \quad (17)$$

With the panel data, one can estimate α_i , unobservable time-invariant individual effects, η_t , time-effects same across households, and β , effects of household

¹⁵ It is, however, arguable that while the results may be sensitive to the functional form assumed, the relative components of the decomposition are not likely to be affected much (Hoddinott and Quisumbing, 2003b).

characteristics or other observable factors on consumption. Using two-way error component model (Baltagi, 2005), equation (17) can be estimated as:

$$c_{it} = X_{it}\beta_i + \eta_t + \alpha_i + v_{it} \quad (18)$$

where v_{it} is an error term which is also independent, and identically distributed (\sim IID $(0, \sigma^2_v)$).

Our purpose is to decompose the total vulnerability arising from poverty and risk into four components using the estimation results for (18). Equation (14) can be rewritten as (14)' by assuming that z -the poverty line- is the mean consumption, and by including in it the unexplained risk and measurement error.

$$\begin{aligned} V_i = & [U_i(E_c) - U_i(Ec_{it})] && \text{(Poverty)} \\ & + \{U_i(Ec_{it}) - EU_i[E(c_i | \bar{x}_t)]\} && \text{(Covariate or Aggregate Risk)} \\ & + \{EU_i[E(c_i | \bar{x}_t)] - EU_i[E(c_i | \bar{x}_t, x_{it})]\} && \text{(Idiosyncratic Risk)} \\ & + \{EU_i[E(c_i | \bar{x}_t, x_{it})] - EU_i(c_i)\} && \text{(Unexplained Risk \& Measurement Error)} \end{aligned} \quad (14)'$$

We can derive various conditional expectations in (14)' to decompose the entire vulnerability measure (or VEU measure) for each household by applying restricted least squares to equation (18) and then substituting each conditional expectation of consumption into (16).

As noted earlier, we use the expenditure data including food and non-food components, created by Gautam (1991) and used by Ravallion and Chaudhuri (1997), since substitution of consumption by income data in (16) is problematic and idiosyncratic income risks in (14) may be insured. Consumption equation, as in (18), should have income if the income data are available as in our case. However, income is likely to be endogenous for various reasons. For example, savings and liquidation of various household assets (e.g. livestock) are likely to influence not only consumption but also income since a part of the assets is used for production purposes. Food consumption affects the productivity of workers and thus increases income through improvements in nutritional status. Hence, in estimating equation (18), we use the Instrumental Variable (IV) specification where income is treated as endogenous. As in Ligon and Schechter (2003), the average consumption of all households is normalised to be unity. As a consequence, if resources are allocated in such a way that there is no vulnerability (i.e. no inequality or poverty and no risk), then each household's utility would be one. Also, if V_i in (14)' is 0.25, then the utility of the average household is 25% less than it would be if resources could be distributed so as to eliminate inequality among households and risk in consumption.

The IV estimation for VEU can be carried out in the same way as for VEP.

$$\text{First stage: } y_{it} = X'_{it}\beta_1 + L'_{it}\beta_2 + H'_{it}\beta_3 + D'_t\beta_4 + \mu_i + e_{it} \quad (19)$$

$$\text{Second Stage: } c_{it} = \gamma_1 y_{it} + X'_{it}\gamma_2 + H'_{it}\gamma_3 + D'_t\gamma_4 + \alpha_i + v_{it} \quad (20)$$

where time effects are replaced by a vector of year dummies, D'_t , for simplicity. L_i , a vector of owned land area, the share of irrigated land, and non-land assets, are used as an instrument. μ_i and α_i are unobserved individual effects. One cannot deny the possibility of the effects of L_i on consumption, but it seems natural to assume that these variables first affect income. Random-effects model is chosen over fixed-effects model through the Hausman specification test in our case. We then compute vulnerability by various conditional expectations of consumption, as in (14)'.

(3) Vulnerability as Uninsured Exposure to Risk (VER)

In the absence of effective risk management strategy, shocks result in welfare loss to the extent that they lead to reduction of consumption. In this sense, it is a consequence of uninsured exposure to risk. VER is designed to assess *ex post* welfare loss from a negative shock (e.g. a flood) as opposed to an *ex ante* assessment of future poverty in VEP¹⁶.

Consider a household, h , residing in a village, v , at time t . Let $\Delta \ln c_{htv}$ denote change in log consumption or the growth rate of consumption per capita of household h between t and $t-1$, and $S(i)_{tv}$ aggregate / covariate shocks and $S(i)_{htv}$ idiosyncratic shocks. Further, let D_v be a set of binary variables identifying each community/village separately, and X be a vector of household characteristics. An estimate of VER could then be obtained as:

$$\Delta \ln c_{itv} = \sum_i \lambda_i S_{tv} + \sum_i \beta_i S_{itv} + \sum_{tv} \delta(D_v) + \delta_v X_{itv} + \Delta \varepsilon_{itv} \quad (21)$$

In the present context, λ and β are of particular interest as they seek to capture the effects of covariate, S_{tv} , and idiosyncratic shocks, S_{itv} , respectively. Note that these effects are net of coping strategies and public responses.

A variant of (21) that has figured prominently in recent studies involves replacing $\sum_i \lambda_i S_{tv}$ and $\sum_i \beta_i S_{itv}$ with $\Delta \left(\overline{\ln y_{vt}} \right)$ - the growth rate of average community/village income-and $\Delta \ln y_{itv}$ -the growth rate of household income, respectively. These variables are supposed to represent the combined effect of all covariate and idiosyncratic shocks.

¹⁶ Contrary to the assertion in Hoddinott and Quisumbing (2003), it is not clear why a straightforward aggregation across individuals is not feasible or worthwhile.

$$\Delta \ln c_{itv} = \alpha + \beta \Delta \ln y_{itv} + \gamma \Delta \left(\overline{\ln y_{vt}} \right) + \delta X_{itv} + \Delta \varepsilon_{htv} \quad (22)$$

Much of the empirical literature has concentrated on verifying whether $\beta = 0$, consistent with complete risk sharing. Although complete risk-sharing is rejected, estimates of β are generally low, suggesting that growth of consumption is related to growth rate of income but less so than under the alternative hypothesis of no risk-sharing. The higher the estimate of β the greater is the vulnerability of consumption to income risk. In our specification we include schooling years of household head, and their squares, caste, and both level and the first difference of household size and their squares in X_{itv} .

One limitation of measures of vulnerability based on equations (21) and (22) is the presumption that positive and negative income shocks have symmetric effects. Ability to deal with such shocks, however, differs in general and between different groups of households. So to interpret β in (22) as a measure of vulnerability, as opposed to a measure of consumption insurance, may be misleading. This could be overcome by replacing $\Delta \ln y_{itv}$ with two measures of positive and negative income changes (Hoddinott and Qisuumbing, 2003b).

In the present study, we use $\Delta \left(\overline{\ln y_{vt}} \right)$ as a proxy for the aggregate shock as in Townsend (1994) and Ravallion and Chaudhuri (1997). We also use the crop shock measure for S_{it} , following Gaiha and Imai (2004). The production shock for each household in the village is measured in terms of a deviation from a semi-logarithmic trend in crop production at the village level *minus* household's own crop income. Village crop income (minus own crop income) at time t , C_{it} , is

$$C_{it} = \sum_{j=1}^{n, j \neq i} c_{jt}$$

where c_{jt} is crop income of household j at t , and n is the number of households in each village. A time trend is fitted to $\ln(C_{it})$, as shown below.

$$\ln(C_{it}) = b_0 + b_1 T \quad (23)$$

A measure of crop shock is then the deviation of the $\ln(C_{it})$ from its trend value, $\ln(\hat{C}_{it})$, as shown in equation (24).

$$S_{it} = \ln(C_{it}) - \ln(\hat{C}_{it}) \quad (24)^{17}$$

IV. Results

We carried out econometric estimation based on the specification in the previous section and obtained vulnerability measures. In this section, we will first briefly discuss the estimation results and then summarise vulnerability measures across different household groups, classified by landholding, educational attainment of household head, and caste.

(1) Vulnerability as Expected Poverty (VEP)

We applied equations (10) and (11) to each annual cross-sectional component of the 10-year panel data along the lines of Chaudhuri, Jalan and Suryahadi (2002). The cross-sectional results are given in Tables 1-1, 1-2, 1-3 and 1-4. Results based on GLS panel data- where cross-sectional heteroscedasticity is modelled as in equation (6)- are shown in the last column of Table 1-4.

The results for log income per capita are generally plausible except that schooling years of household head is not significant in most cases. Only in 1982 and 1983 (in Table 1-3), schooling years are positive and significant at the 10% level. Age of household head is positive and significant and its square is negative and significant reflecting that households with older heads tend to have higher income per capita, but this positive effect weakens with age.

¹⁷ Crop shocks occur at different times in a year, given the diversity of cropping systems in the sample villages. As shown in Appendix 1, traditional cropping systems embrace the rainy season cereal/pulse intercrop in Aurepalle and the post-rainy season sorghum systems in Shirapur and Kalman. What is also observed is irrigated paddy production in Dokur and Aurepalle and hybrid sorghum in Kanzara and Kinkheda (Gaiha and Imai, 2004). As shown in Figures 1 and 2 in Appendix 2, the crop shocks in the sample villages in Andhra Pradesh and Maharashtra over the period 1975-84 were frequent and large. What is also striking is that, while these shocks were similar in the Maharashtra villages, this was not the case in the Andhra Pradesh villages. In the latter, not just the intensity but also the pattern varied significantly. For example, a large negative shock in one village coincided with a large positive shock in another. Considering that large fractions of households depend on agriculture as the main source of livelihood, such shocks are bound to have significant effects on household incomes (*ibid.*, 2004).

Table 1-1 Results for VEP (Vulnerability as Expected Poverty) Measure (1975-77)

Dep. Variable	1975				1976				1977			
	log (income per capita)		variance		log (income per capita)		log (income per capita)		variance			
	β	θ	β	θ	β	θ	β	θ				
	Coef.	t value	Coef.	t value	coef.	t value	coef.	t value	coef.	t value		
Xi												
age of household head	0.0135	(0.82)	-0.0151	(-0.20)	0.0149	(0.68)	0.0050	(0.24)	-0.0380	(-0.41)		
age of household head squared	-0.0001	(-0.80)	0.0001	(0.12)	-0.0002	(-0.75)	0.0000	(0.11)	0.0004	(0.41)		
Household size	-0.1767	(-3.54) **	-0.3035	(-1.64)	-0.2606	(-4.50) **	-0.2686	(-6.31) **	0.0506	(0.25)		
Household size squared	0.0060	(1.75) +	0.0136	(1.15)	0.0117	(3.30) **	0.0105	(3.98) **	-0.0010	(-0.09)		
Caste dummies (high)	0.1909	(1.85) +	0.6303	(1.30)	0.3880	(2.65) **	-0.0491	(-0.40)	0.3082	(0.53)		
(middle high)	0.3610	(3.88) **	0.2954	(0.62)	0.4097	(2.96) **	0.2630	(2.41) *	-0.1341	(-0.24)		
(middle low)	0.1531	(1.57)	0.8427	(1.87) +	0.1167	(0.79)	-0.0329	(-0.30)	0.0248	(0.05)		
Li												
Owned area of land	0.0848	(4.56) **	0.0102	(0.14)	0.0202	(0.73)	0.0798	(4.30) **	-0.1109	(-1.22)		
Owned area squared	-0.0016	(-2.48) *	-0.0002	(-0.08)	-0.0009	(-0.84)	-0.0019	(-3.07) **	0.0016	(0.53)		
Share of irrigated land	0.0037	(4.08) **	-0.0050	(-1.03)	0.0042	(2.66) **	0.0048	(3.16) **	0.0022	(0.34)		
Non-land production assets	0.0000	(2.32) *	0.0001	(1.69) +	0.0001	(2.85) **	0.0001	(3.22) **	0.0001	(1.59)		
Non-land assets squared	0.0000	(-1.28)	0.0000	(-1.71) +	0.0000	(-0.81)	0.0000	(-1.00)	0.0000	(-1.28)		
Hi												
Schooling yrs of hh head	-0.0006	(-0.02)	0.2595	(2.16) *	0.0275	(0.61)	0.0551	(1.56)	-0.0645	(-0.44)		
Schooling yrs squared	0.0030	(1.80) +	-0.0283	(-2.46) *	-0.0028	(-0.56)	-0.0045	(-1.12)	0.0079	(0.58)		
constant	6.0888	(13.90)	-1.8822	(-1.03)	6.6271	(12.71)	7.0189	(14.01)	-2.5422	(-1.12)		
No. of Observations	198		198		200		198		198			
F	21.74	**	1.53		11.96	**	16.31		0.45			
R squared	0.6245		0.1045		0.4695		0.5551		0.0340			

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 1-2 Results for VEP (Vulnerability as Expected Poverty) Measure (1978-80)

Dep. Variable	1978				1979				1980			
	log (income per capita)		variance		log (income per capita)		variance		log (income per capita)		variance	
	β	θ	β	θ	β	θ	β	θ	β	θ	β	θ
	Coef.	t value	Coef.	t value	coef.	t value	coef.	t value	coef.	t value	coef.	t value
Xi												
age of household head	0.0108	(0.54)	0.0172	(0.19)	0.0053	(0.27)	0.0338	(1.15)	-0.1168	(-1.22)		
age of household head squared	0.0000	(-0.07)	-0.0001	(-0.16)	0.0000	(0.20)	-0.0002	(-0.84)	0.0012	(1.34)		
Household size	-0.2135	(-4.47) **	0.0109	(0.05)	-0.2194	(-4.77) **	-0.0816	(-1.87) +	-0.0877	(-0.47)		
Household size squared	0.0070	(2.33) *	0.0002	(0.01)	0.0076	(2.82) **	0.0011	(0.47)	0.0016	(0.15)		
Caste dummies (high)	0.1976	(1.61)	0.5528	(1.01)	0.3507	(2.94) **	0.2084	(1.62)	-0.0990	(-0.18)		
(middle high)	0.2552	(2.32) *	0.1801	(0.34)	0.2695	(2.64) **	0.2052	(1.73) +	0.0626	(0.12)		
(middle low)	0.2439	(2.21) *	0.3591	(0.71)	0.1069	(0.99)	-0.0468	(-0.38)	0.1696	(0.34)		
Li												
Owned area of land	0.0519	(2.85) **	0.0155	(0.18)	0.0819	(4.04) **	0.0203	(0.82)	-0.0486	(-0.56)		
Owned area squared	-0.0009	(-1.78) +	-0.0014	(-0.50)	-0.0020	(-2.89) **	-0.0003	(-0.32)	0.0015	(0.44)		
Share of irrigated land	0.0068	(4.36) **	0.0042	(0.67)	0.0069	(5.97) **	0.0038	(1.98) *	0.0136	(2.73) **		
Non-land production assets	0.0001	(3.57) **	0.0000	(-0.26)	0.0000	(2.78) **	0.0000	(2.27) *	0.0001	(2.05) *		
Non-land assets squared	0.0000	(-1.91) +	0.0000	(-0.48)	0.0000	(-2.21) *	0.0000	(-0.89)	0.0000	(-1.70) +		
Hi												
Schooling yrs of hh head	0.0239	(0.68)	-0.1193	(-0.87)	0.0285	(0.79)	-0.0334	(-1.09)	-0.1071	(-0.80)		
Schooling yrs squared	-0.0032	(-0.81)	0.0150	(1.16)	-0.0034	(-0.80)	0.0018	(0.63)	0.0054	(0.42)		
constant	6.6375	(13.32)	-3.4747	(-1.56)	6.7105	(13.10)	5.6488	(7.49)	-0.1237	(-0.05)		
No. of Observations	197		197		196		196		196		196	
F	24.25	**	0.41		28.61	**	4.50	**	1.45			
R squared	0.6510		0.0400		0.6888		0.2583		0.2182			

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 1-3 Results for VEP (Vulnerability as Expected Poverty) Measure (1981-83)

Dep. Variable	1981				1982				1983			
	log (income per capita)		variance		log (income per capita)		variance		log (income per capita)		variance	
	β	θ			β	θ	β	θ				
	Coef.	t value	Coef.	t value	coef.	t value	coef.	t value	coef.	t value	coef.	t value
Xi												
age of household head	0.0466	(1.44)	-0.2015	(-2.27) *	0.0788	(2.75) **	0.0346	(1.51)	0.0487	(0.48)		
age of household head squared	-0.0004	(-1.34)	0.0018	(2.17) *	-0.0007	(-2.68) **	-0.0003	(-1.59)	-0.0005	(-0.57)		
Household size	-0.1218	(-3.45) **	0.2270	(1.47)	-0.1872	(-6.84) **	-0.1334	(-4.58) **	0.1538	(1.08)		
Household size squared	0.0026	(1.69) +	-0.0197	(-2.28) *	0.0059	(5.18) **	0.0023	(1.92) +	-0.0074	(-1.03)		
Caste dummies (high)	0.0299	(0.24)	-0.2172	(-0.46)	0.2699	(2.46) *	0.0542	(0.49)	0.1073	(0.21)		
(middle high)	0.1070	(0.88)	-0.1174	(-0.26)	0.2664	(2.64) **	0.2909	(2.52) *	0.3196	(0.63)		
(middle low)	-0.1632	(-1.18)	0.5152	(1.15)	-0.0093	(-0.08)	-0.0408	(-0.34)	0.6130	(1.24)		
Li												
Owned area of land	0.0482	(2.03) *	-0.0019	(-0.02)	0.0533	(2.68) **	0.1132	(4.97) **	0.0072	(0.08)		
Owned area squared	-0.0018	(-2.32) *	-0.0013	(-0.41)	-0.0020	(-2.01) *	-0.0026	(-3.30) **	-0.0009	(-0.25)		
Share of irrigated land	0.0055	(4.03) **	0.0014	(0.30)	0.0032	(3.51) **	0.0042	(2.94) **	0.0018	(0.33)		
Non-land production assets	0.0000	(4.13) **	0.0001	(2.10) *	0.0000	(4.99) **	0.0000	(0.12)	0.0000	(0.72)		
Non-land assets squared	0.0000	(-3.68) **	0.0000	(-0.96)	0.0000	(-5.11) **	0.0000	(1.63)	0.0000	(-0.99)		
Hi												
Schooling yrs of hh head	0.0267	(0.80)	-0.1195	(-1.03)	0.0526	(1.76) +	0.0539	(1.75) +	-0.0487	(-0.38)		
Schooling yrs squared	-0.0036	(-0.98)	0.0071	(0.63)	-0.0037	(-1.00)	-0.0025	(-0.78)	0.0014	(0.11)		
constant	5.4574	(6.33)	2.0132	(0.84)	5.0376	(6.73)	6.1234	(9.34)	-4.6948	(-1.64)		
No. of Observations	197		197		197		198		198			
F	7.72	**	1.81		22.89	**	12.29	**	0.51			
R squared	0.3726		0.1219		0.6378		0.4846		0.0378			

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 1-4 Results for VEP Measure (1984 & panel estimation for 1976-84)

Dep. Variable	1984				GLS Panel Estimation	
	log (income per capita)		variance		log (income per capita)	
	β Coef.	t value	θ Coef.	t value	β coef.	t value
Xi						
age of household head	0.0509	(2.05) *	0.0889	(0.73)	0.0209	(3.75) **
age of household head squared	-0.0005	(-2.43) *	-0.0010	(-0.93)	-0.0002	(-2.97) **
Household size	-0.1493	(-4.23) **	-0.0241	(-0.13)	-0.1841	(-17.56) **
Household size squared	0.0039	(2.57) *	-0.0048	(-0.50)	0.0056	(9.23) **
Caste dummies (high)	-0.0138	(-0.10)	0.5582	(0.92)	0.2223	(7.03) **
(middle high)	0.2728	(2.19) *	0.0638	(0.10)	0.2894	(9.96) **
(middle low)	0.1067	(0.78)	0.6775	(1.16)	0.0689	(2.24) *
Li						
Owned area of land	0.0455	(1.32)	0.0119	(0.09)	0.0694	(12.71) **
Owned area squared	-0.0013	(-1.19)	0.0015	(0.33)	-0.0015	(-7.14) **
Share of irrigated land	0.0019	(0.53)	0.0172	(1.72) +	0.0031	(9.02) **
Non-land production assets	0.0000	(3.39) **	0.0000	(0.79)	0.0000	(14.49) **
Non-land assets squared	0.0000	(-2.05) *	0.0000	(-1.62)	0.0000	(-8.47) **
Hi						
Schooling yrs of hh head	-0.0282	(-0.79)	-0.2595	(-1.77) +	0.0083	(1.05)
Schooling yrs squared	0.0056	(1.37)	0.0222	(1.62)	0.0000	(0.00)
constant	5.7466	(7.85)	-4.6059	(-1.33)	6.3717	(45.03)
No. of Observations	119		119		1,896	
F	17.68	**	1.39		Wald Chi ² (13)	
R squared	0.7042		0.1575		Log likelihood -1,285	

Notes: 1. ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10%

2. In 1984 the data are available for only three villages, Aurepalle, Shirapur and Kanz

3. Estimation results for variance in the case of panel regression are not provided by the program

Caste dummies are significant in the panel regression. In particular, ‘high caste’ and ‘middle high castes’ have generally positive and significant coefficients in cross-sectional regressions except in a few years. Owned area of land has a positive and significant effect while its square has a negative and significant effect in both cross-sectional regressions (except in 1976, 80, and 84) and GLS panel results. As expected, both share of irrigated area and non-land production assets have positive and significant effects.

The regression results on variance of log income per capita are not stable over time. However, it is noted that variance is influenced by some household characteristics, such as household size and its square (e.g. the effect of the former is negative and significant in 1976 while that of the latter is positive and significant) non-land production assets (e.g. the former is positive and significant in 1982, but the coefficient is small), and schooling years of household head and its square (e.g. the former is positive and significant in 1975, and the latter is negative and significant). Thus the Chaudhuri- Jalan - Suryahadi specification (2002) yields plausible results.

The VEP measure is then constructed for each household by the cross sectional regression for each year and also by the panel regression. We will compare VEP measures with VEU measures across different groups of households later in this section.

(2) Vulnerability as Low Expected Utility (VEU)

Table 2 provides results of IV estimation for equations (19) and (20). Since differences between coefficients of the fixed effects IV model and the random effects model are *not* systematic at the 5% level, using the Hausman test, the random effects IV model is preferred (Baltagi 2005). The first stage regression on the normalized household income yields results similar to the panel regression in Table 1-4 except that high caste dummy does not have a significant positive coefficient.¹⁸ In the second stage, normalised household consumption (i.e. consumption which is normalized so that the mean is unity) is estimated by normalized household income. The coefficient of household income is positive and highly significant, implying that, if income increases by one unit, consumption will increase by 0.5524. High caste households tend to consume more than the rest. These estimation results are used to derive various expectations of consumption in (14)’, using restricted least squares, and then these expectations are converted into utility (16).

Table 3-1 shows the decomposition of the VEU measure. 0.7476 in the head of the second column is our estimate of the vulnerability of the whole households. It is not necessarily easy to give it an intuitive interpretation, but this implies that the utility of the average household is 75% less than the hypothetical situation without any risk or inequality in consumption.

¹⁸ It is because significant coefficient of ‘high caste’ in the second stage in turn has affected the first stage in the iterative estimation.

**Table 2 Results for VEU (Vulnerability as Expected Low Utility) Measure
G2SLS Random-Effects IV Regression for Panel Data in 1975-84**

Dep. Variable	First Stage		Second Stage	
	Normalised household income		Normalised household consumption	
	β Coef.	t value	γ coef.	t value
Y_{it}				
Normalised income per capita	-	-	0.5524	(8.31) **
X_{it}				
Age of household head	0.0526	(4.39) **	0.0068	(0.30)
Age of household head squared	-0.0005	(-4.56) **	-0.0001	(-0.27)
Household size squared	-0.1671	(-7.66) **	-0.0414	(-1.04)
Household size squared	0.0038	(3.11) **	0.0011	(0.51)
Caste dummies (high)	-0.0398	(-0.55)	0.2450	(1.96) +
(middle high)	0.2801	(3.90) **	0.0237	(0.18)
(middle low)	0.0910	(1.36)	0.0528	(0.43)
L_i				
Owned area of land	0.0791	(6.49) **	-	-
Owned area squared	-0.0020	(-5.26) **	-	-
Share of irrigated land	0.0045	(3.59) **	-	-
Non-land production assets	0.0000	(11.39) **	-	-
Non-land assets squared	0.0000	(-3.15) **	-	-
H_i				
Schooling yrs of hh head	0.0176	(1.07)	0.0053	(0.18)
Schooling yrs squared	-0.0011	(-0.79)	-0.0007	(-0.26)
D_t				
Whether in the crop year 1976	0.0733	(0.93)	-0.1375	(-0.95)
Whether in the crop year 1977	0.2848	(3.62) **	0.0937	(0.64)
Whether in the crop year 1978	0.1692	(2.14) *	-0.2052	(-1.41)
Whether in the crop year 1979	0.2704	(3.38) **	-0.1324	(-0.89)
Whether in the crop year 1980	0.2136	(2.64) **	-0.1285	(-0.86)
Whether in the crop year 1981	0.5263	(6.37) **	-0.1676	(-1.07)
Whether in the crop year 1982	0.6914	(8.26) **	-0.8669	(-5.32) **
Whether in the crop year 1983	0.8348	(9.79) **	-0.7004	(-4.08) **
Whether in the crop year 1984	0.7745	(8.70) **	-0.6574	(-3.77) **
constant	-0.4726	(-1.53)	0.6220	(1.09)
No. of observations		1184		1184
Wald $\chi^2(22)$	Wald $\chi^2(22)$	1020	Wald $\chi^2(13)$	142
Hausman test for the choice between fixed effects IV model and random effects IV model	$\chi^2 =$	19.57		
	Prob> $\chi^2 =$	0.297		

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 3-1 Decomposition of VEU (Vulnerability as Expected Low Utility) and Its Determinants

Regression of each vulnerability measure on time-series means of household variables (between estimator)

Average Value	VEU		= Poverty		+ Agg Risk		+ Idio Risk		+ Unexp Risk	
	0.7476	=	0.2586	+	0.1671	+	0.2750	+	0.0470	
	Coef.	t value	Coef.	t value	coef.	t value	coef.	t value	coef.	t value
Xi										
age of household head	-0.1903	(-2.31) *	-0.0876	(-2.50) *	0.0361	(0.68)	-0.0128	(-0.09)	-0.1260	(-1.18)
age of household head squared	0.0017	(2.11) *	0.0008	(2.28) *	-0.0003	(-0.52)	0.0000	(-0.02)	0.0012	(1.17)
Household size squared	0.3246	(1.81) +	0.2291	(3.00) **	0.0024	(0.02)	0.1460	(0.49)	-0.0529	(-0.23)
Household size squared	-0.0019	(-0.18)	-0.0081	(-1.75) +	-0.0006	(-0.08)	0.0036	(0.20)	0.0031	(0.22)
Caste dummies (high)	0.0357	(0.07)	-0.2194	(-1.07)	-0.5049	(-1.62)	0.8656	(1.07)	-0.1056	(-0.17)
(middle high)	-0.0721	(-0.15)	-0.2305	(-1.13)	-0.0643	(-0.21)	-0.0208	(-0.03)	0.2435	(0.39)
(middle low)	0.5487	(1.27)	-0.0123	(-0.07)	-0.4380	(-1.58)	1.5197	(2.11) *	-0.5207	(-0.94)
Li										
Owned area of land	-0.1570	(-1.53)	-0.0411	(-0.94)	0.0666	(1.01)	-0.2983	(-1.74) +	0.1158	(0.87)
Owned area squared	0.0040	(1.35)	0.0013	(1.05)	-0.0015	(-0.78)	0.0071	(1.44)	-0.0030	(-0.78)
Share of irrigated land	-0.0006	(-0.04)	-0.0029	(-0.48)	-0.0023	(-0.25)	0.0034	(0.15)	0.0012	(0.06)
Non-land production assets	-0.0001	(-1.19)	-0.0001	(-2.69) **	0.0000	(-0.33)	0.0000	(0.17)	0.0000	(-0.09)
Non-land assets squared	0.0000	(1.20)	0.0000	(2.16) *	0.0000	(0.23)	0.0000	(0.19)	0.0000	(-0.15)
Hi										
Schooling yrs of hh head	-0.1259	(-0.95)	-0.0293	(-0.52)	0.0478	(0.56)	-0.1844	(-0.83)	0.0401	(0.23)
Schooling yrs squared	0.0063	(0.57)	0.0017	(0.37)	-0.0057	(-0.81)	0.0128	(0.69)	-0.0024	(-0.17)
constant	4.7809	(2.25)	2.2663	(2.51)	-0.7829	(-0.57)	0.1343	(0.04)	3.1633	(1.15)
No. of Observations	1184		1184		1184		1184		1184	
Joint Significance: F (14, 117)	2.73	**	4.23	**	0.64		0.91		0.38	
R squared	0.1874		0.3358		0.0542		0.0758		0.0381	

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Of course, the results are derived by a specific form of utility function (16) that may not necessarily reflect individual preferences. However, our estimate suggests a potentially very large effect of inequality and poverty on household utility. Our estimate of $VEU=0.7476$ is much larger than the Bulgarian estimate of 0.1972, reported by Ligon and Schechter (2003). It is surmised that this large difference is due to the larger magnitudes of risk and inequality of consumption in rural India, and the fact that we use annual consumption data in rural area for 10 years and Ligon and Schechter (2003) use monthly consumption data for 12 months.

An important finding is that the vulnerability arising from risk (0.4426; 59% of the total vulnerability), as the sum of aggregate 0.1671 (22%) and idiosyncratic risks, 0.2750 (37%), is very large. Indeed, it is even larger than the vulnerability associated with poverty, 0.2586 (35%). This is in sharp contrast with Ligon and Schechter's (2003) finding where the corresponding risk component is 0.0279 (14% of the total vulnerability), as the sum of the aggregate (0.0264; 13%) and idiosyncratic risks, (0.0014; 1%). The vulnerability associated with poverty is also large in our case (0.2586; 35 %), much larger than that in Bulgaria, 0.1079 (31% of the total vulnerability).

Our results are different from Ligon's (2005), based on the ICRISAT data for three villages, Aurepalle, Shirapur, and Kanzara, for 1976-81. The latter show that (i) idiosyncratic risk for consumption is generally small, as it ranged from 2 to 4 % of the total risk (*i.e.*, sum of aggregate idiosyncratic risks, and unexplained risk and measurement errors); (ii) aggregate risk is large except in Shirapur (58% of total risk in Aurepalle, 5% in Shirapur, and 26% in Kanzara); and (iii) unexplained risk is large in all three villages (38% of the total risk in Aurepalle, 88% in Shirapur, and 60% in Kanzara). These results are different for the following reasons: (i) we have used adjusted consumption data, corrected for measurement errors, while Ligon (2005) has used unadjusted data; (ii) our specifications differ from Ligon's (2005);¹⁹ (iii) all three villages are considered together for 1975-84 in our analysis, while Ligon (2005) considers each village separately for 1976-81. Although the sum of idiosyncratic and unexplained risks in the total risk is similar (66% in our case and 70% in Ligon's (2005)), it is surmised that some unexplained risks and measurement errors in Ligon's (2005) analysis are in fact idiosyncratic risks, as reported in our study.

Although generalizations of our findings to different settings is not straightforward, our analysis suggests that vulnerability associated with idiosyncratic and aggregate shocks have a significant negative impact on a household's well-being. Our analysis also suggests that completely insuring against idiosyncratic risks has a larger impact on the average utility of households than completely eliminating inequality.

In another exercise, we regress each component of vulnerability on time series means of various household characteristics to explore the determinants of vulnerability in

¹⁹ We have used IV estimates of household income whereas Ligon (2005) has employed the Newey-West estimator whereby the cross-sectional correlation is adjusted but does not instrument income in the consumption function.

Table 3-1. A household headed by an older member has lower (total) VEU measure because of lower vulnerability associated with poverty. On the other hand, a larger household tends to have a higher VEU measure because of the higher poverty measure. Also, the more non-land production assets a household has, the lower is the VEU measure of poverty. Turning to aggregate shocks, households in high caste and in middle low caste tend to be less vulnerable to them. Households in middle low caste and those with lower owned land are more vulnerable to idiosyncratic shocks. This suggests that the landless or small farmers tend to be vulnerable to idiosyncratic shocks resulting in reduced consumption.

We have carried out regressions for estimated VEP measures and static poverty measure using the same specification to do comparisons of determinants of different vulnerability measures and static poverty (Table 3-2). Static poverty can be simply defined by comparing log household income per capita with a poverty threshold of Rs 180 per capita of income per year at 1960-61 prices. Static poverty is estimated by fixed-effects probit model.

It is noted that determinants of poverty and those of VEP measures are quite similar. In particular, land holding is crucial in both poverty reduction and reduction of vulnerability. Non-land assets also reduce poverty and vulnerability. However, having an older person as a household head is significant in reducing the cross-sectional VEP measure and VEU measure, but it is not significant in poverty reduction. On the other hand, caste is one of the significant determinants of poverty, but not of vulnerability (i.e. VEU and cross-sectional VEP). Surprisingly, variables on schooling years of head are not significant.

(3) Vulnerability as Uninsured Exposure to Risk (VER)

The results for VER are presented in Table 4. We estimate equations (21) and (22) by applying random-effects GLS²⁰ to the annual data for three sample villages, Aurepalle, Shirapur and Kanzara. The specification in Case A of each column is same as in Ravallion and Chaudhuri (1997) except that we have added household characteristics.

The results in Case A are generally consistent with Ravallion and Chaudhuri (1997). Complete risk sharing hypothesis (i.e. $\beta = 0$ where β is the coefficient of $\Delta(\ln y_{vy})$) is not rejected in Aurepalle (which implies that risk is shared among households in this village). In Shirapur and Kanzara, β is negative and significant. That is, in bad time, the consumption is well (or over) insured in these villages.

²⁰ The Hausman test suggests that random effects model should be preferred to fixed effects model in all cases in Table 4.

Table 3-2 Determinants of VEP (Vulnerability as Expected Poverty) measure and Static Poverty

	VEP (based on cross-sectional data)		VEP (based on panel data)		Poverty (static binary variable)	
	Fixed-effects model		Fixed effects model		Fixed effects probit model	
	Coef.	t value	Coef.	t value	Coef.	t value
Xi						
age of household head	-0.0456	(-4.11) **	-0.0108	(-1.10)	-0.0595	(-1.42)
age of household head squared	0.0002	(1.57)	0.0000	(-0.45)	0.0005	(1.31)
Household size squared	0.1687	(11.09) **	0.2038	(15.13) **	0.3140	(5.25) **
Household size squared	-0.0063	(-7.97) **	-0.0073	(-10.48) **	-0.0078	(-2.69) **
Caste dummies (high)	-0.1513	(-1.07)	-0.4644	(-3.69) **	-0.4637	(-2.05) *
(middle high)	0.1243	(1.00)	-0.2384	(-2.17) *	-0.5790	(-2.55) *
(middle low)	-	-	-	-	-0.3556	(-1.70) +
Li						
Owned area of land	-0.0426	(-4.46) **	-0.0607	(-7.18) **	-0.1444	(-3.74) **
Owned area squared	0.0006	(1.89) +	0.0009	(3.07) **	0.0027	(2.21) *
Share of irrigated land	-0.0024	(-3.94) **	-0.0026	(-4.76) **	-0.0052	(-1.19)
Non-land production assets	0.0000	(-3.33) **	0.0000	(-7.04) **	0.0000	(-2.26) *
Non-land assets squared	0.0000	(3.80) **	0.0000	(6.76) **	0.0000	(-0.35)
Hi						
Schooling yrs of hh head	-0.0126	(-1.14)	0.0071	(0.72)	0.0215	(0.37)
Schooling yrs squared	0.0011	(1.07)	-0.0015	(-1.67)	-0.0034	(-0.67)
constant	1.7697	(6.00)	0.7258	(2.78)	1.1602	(1.08)
No. of Observations	1181		1181		1181	
Joint Significance Test	F(13, 1036)=	36.04 **	F(13, 1036)=	51.51 **	Wald Chi ² (14)=	118.01 **
Hausman Test for the choice b	Chi2(11)=	86.03**	Chi2(11)=	21.01**	N/A	
R squared	0.2799		0.5942		0.2488	Pseudo R ²)

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 4 Results for VER (Vulnerability as Uninsured Exposure to Risk)
GLS Random-effects GLS for Panel Data for 1975-84

	Dep. Variable: $\Delta \ln c_{it}$: First Difference of log consumption											
	Aurepalle				Shirapur				Kanzara			
	Case A		Case B		Case A		Case B		Case A		Case B	
	Village mean of log income used		Crop shock measure used		Village mean of log income used		Crop shock measure used		Village mean of log income used		Crop shock measure used	
Coef.	t value	Coef.	t value	coef.	t value	coef.	t value	coef.	t value	coef.	t value	
$\Delta \ln y_{it}$: First Difference of log income	0.2065	(5.34) **	0.2185	(5.32) **	0.0974	(2.39) *	0.0717	(-1.83) +	0.5383	(4.91) **	0.3999	(3.63) **
$\Delta \ln y_{it}$ First dif. of village mean of log income	0.0887	(0.94)	-	-	-0.4539	(-3.86) **	-	-	-1.3910	(-4.46) **	-	-
Crop shock variable	-	-	0.1753	(3.02) **	-	-	-0.7198	(-3.40) **	-	-	-0.3234	(-1.30)
Schooling yrs of hh head	0.0361	(0.85)	0.0311	(0.74)	0.0153	(0.62)	0.0204	(0.82)	0.0046	(0.14)	0.0032	(0.09)
Schooling yrs squared	-0.0012	(-0.27)	-0.0008	(-0.20)	-0.0013	(-0.71)	-0.0018	(-0.95)	0.0002	(0.07)	0.0004	(0.11)
Household size	-0.0131	(-0.31)	-0.0104	(-0.25)	-0.0266	(-0.55)	-0.0299	(-0.61)	-0.0146	(-0.38)	-0.0129	(-0.32)
Household size squared	0.0003	(0.10)	0.0002	(0.08)	0.0012	(0.43)	0.0014	(0.48)	0.0010	(0.48)	0.0009	(0.41)
Δ Household size	-0.2162	(-2.83) **	-0.2066	(-2.73) **	-0.2568	(-2.20) *	-0.2683	(-2.29) *	0.0513	(0.43)	-0.0222	(-0.18)
[Δ Household size] squared	0.0046	(0.87)	0.0034	(0.66)	0.0101	(1.70) +	0.0104	(1.74) +	-0.0060	(-0.85)	-0.0039	(-0.54)
Caste dummies (high)	-0.1695	(-1.31)	-0.1650	(-1.30)	0.0228	(0.21)	0.0196	(0.18)	-0.0752	(-0.48)	-0.0797	(-0.47)
(middle high)	-0.2521	(-1.57)	-0.2358	(-1.50)	0.1025	(0.54)	0.1081	(0.57)	-0.0516	(-0.48)	-0.0472	(-0.42)
(middle low)	-0.0228	(-0.34)	-0.0180	(-0.27)	-0.0340	(-0.28)	-0.0490	(-0.40)	-0.0667	(-0.43)	-0.0546	(-0.34)
constant	0.1121	(0.78)	0.0998	(0.70)	0.1265	(0.63)	0.1501	(0.74)	0.1124	(0.77)	0.0097	(0.06)
No. of Observations	351		347		349		345		351		346	
Joint Significance: Wald $\chi^2(11)=$	110.29 **		117.41		28.17 **		25.66 **		41.91 **		23.57 *	
Hausman Test for the choice between Random & Fixed-eff	4.68		4.47		3.31		3.30		1.74		1.97	
Model: $\chi^2(11)=$												
R squared	0.2455		0.2595		0.0771		0.0715		0.1100		0.0695	

Notes: ** indicates the coefficient is significant at 1% level. * = significant at 5% level. + = significant at 10% level.

In Case B where we use the crop shock measure instead of $\Delta(\overline{\ln y_{vy}})$, in Aurepalle, consumption is significantly reduced in the event of a negative shock and *vice versa*. Hence there is no insurance against a crop shock. However, in both Shirapur and Kanzara, β is negative and significant, implying that some sort of risk-insurance mechanism was in place in these two villages.

This raises the issue why VEU arising from idiosyncratic risks is so high *despite* risk sharing mechanisms? One possibility is that income risk is so large that risk-sharing can reduce only a part of the idiosyncratic shocks. Even if there is a constant consumption over the years to completely eliminate the idiosyncratic VEU, consumption will still vary as risk-sharing ceases to be effective when aggregate shocks occur. Moreover, some aggregate shocks (e.g. earthquakes) cannot be insured against.

(4) Vulnerability across Different Groups

Tables 5-1 and 5-2 contain descriptive statistics and a correlation matrix of vulnerability measures. “POVERTY” denotes static poverty measured by the head-count index (i.e proportion of household’s with a per capita income below a cut-off point, z). It is not surprising that the correlation between “POVERTY” and “VEU_POVERTY” is high (the coefficient being 0.52), but it must be noted that “POVERTY” is not highly correlated with “VEU_AGGREGATE” or “VEU_IDIOSYNCRATIC”. But the VEP measure (an *ex ante* measure), obtained from a cross-section regression as well as from a panel using GLS, is highly correlated with “POVERTY” (with correlation coefficients of 0.57 and 0.48, respectively). A valid inference therefore is that while poverty is *related* to but *distinct* from vulnerability. So also *ex ante* (VEP) and *ex post* measures (VEU)of vulnerability are *related* but *distinct* concepts. Their correlations (i.e. 0.25 to 0.26) are not high but non-negligible.

Table 5-1 Descriptive Statistics of Vulnerability Measures

Variable	Obs	Mean	Std. Dev.	Min	Max
VEP (based on each cross sectional data)	1181	0.498	0.429	0.000	1.000
VEP_GLS (based on panel data)	1181	0.479	0.480	0.000	1.000
POVERTY (static measure of poverty)	1181	0.477	0.500	0.000	1.000
VEU	1181	0.748	1.739	-0.547	18.050
VEU_POVERTY	1181	0.259	0.556	-0.801	6.917
VEU_AGGREGATE	1181	0.167	0.828	-6.425	4.397
VEU_IDIOSYNCRATIC	1181	0.275	2.749	-6.380	21.051
VEU_UNEXPLAINED	1181	0.047	2.095	-20.344	3.533

Table 5-2 Correlation Matrix of Vulnerability and Other Household Characteristics

	VEP	VEP_GLS	POVERTY	VEU	VEU_POV	VEU_AGG	VEU_IDIO	VEU_UNEX	school	ownarea	lowcast	midcast	midhcast	highcast
VEP	1.00													
VEP_GLS	0.80	1.00												
POVERTY	0.57	0.48	1.00											
VEU	0.26	0.25	0.27	1.00										
VEU_POVERTY	0.54	0.54	0.52	0.41	1.00									
VEU_AGGREGATE	0.11	0.12	0.08	-0.24	-0.10	1.00								
VEU_IDIOSYNCRATIC	0.10	0.10	0.09	0.59	0.19	-0.42	1.00							
VEU_UNEXPLAINED	-0.10	-0.12	-0.06	0.04	-0.13	-0.01	-0.71	1.00						
school	-0.31	-0.30	-0.21	-0.14	-0.25	-0.10	-0.08	0.09	1.00					
ownarea	-0.42	-0.42	-0.32	-0.17	-0.43	-0.03	-0.08	0.08	0.44	1.00				
lowcast	0.36	0.39	0.25	0.04	0.32	0.14	-0.06	-0.02	-0.29	-0.29	1.00			
midcast	0.12	0.09	0.02	0.16	0.04	-0.04	0.19	-0.12	-0.21	-0.16	-0.30	1.00		
midhcast	-0.06	-0.04	0.00	-0.05	-0.03	0.12	-0.10	0.05	0.04	-0.07	-0.27	-0.26	1.00	
highcast	-0.37	-0.40	-0.24	-0.14	-0.30	-0.19	-0.03	0.09	0.42	0.46	-0.41	-0.39	-0.35	1.00

Tables 5-3 and 5-4 summarise means of various vulnerability measures by land-holding class, household head's schooling years, and caste. Here are some observations.

- (a) The landless or small farmers are more vulnerable than larger farmers. In particular, small farmers face large idiosyncratic consumption risk.
- (b) A household headed by a person without education is much more vulnerable and poorer than that headed by a person with some education. However, increasing schooling years does not have a dramatic effect on vulnerability.
- (c) Households in lower castes are more vulnerable than those in higher/upper castes.
- (d) If households are landless and at the same time without education or in low castes, they are highly vulnerable to aggregate shocks.

Table 5–3 Comparisons of Vulnerability across Different Groups

Variable	Land-holding status			
	Landless	Small farmers	Middle Farmers	Large Farmers
VEP (based on each cross sectional data)	0.643	0.632	0.511	0.195
VEP_GLS (based on panel data)	0.604	0.631	0.513	0.163
POVERTY (static measure of poverty)	0.671	0.571	0.498	0.156
VEU	0.905	1.213	0.615	0.208
VEU_POVERTY	0.559	0.363	0.229	-0.150
VEU_AGGREGATE	0.267	0.023	0.371	0.052
VEU_IDIOSYNCRATIC	0.264	0.965	-0.343	0.051
VEU_UNEXPLAINED	-0.186	-0.138	0.358	0.254

Variable	Household Head's Schooling Years		
	0	<=5	>5
VEP (based on each cross sectional data)	0.622	0.362	0.293
VEP_GLS (based on panel data)	0.597	0.373	0.250
POVERTY (static measure of poverty)	0.569	0.351	0.359
VEU	1.010	0.396	0.407
VEU_POVERTY	0.396	0.060	0.100
VEU_AGGREGATE	0.204	0.106	0.137
VEU_IDIOSYNCRATIC	0.543	-0.026	-0.157
VEU_UNEXPLAINED	-0.133	0.257	0.327

Variable	Caste			
	Low	Middle-low	Middle-high	high
VEP (based on each cross sectional data)	0.769	0.591	0.442	0.280
VEP_GLS (based on panel data)	0.815	0.560	0.434	0.216
POVERTY (static measure of poverty)	0.701	0.496	0.476	0.309
VEU	0.881	1.250	0.579	0.423
VEU_POVERTY	0.574	0.303	0.225	0.029
VEU_AGGREGATE	0.367	0.109	0.376	-0.049
VEU_IDIOSYNCRATIC	-0.039	1.272	-0.268	0.148
VEU_UNEXPLAINED	-0.020	-0.433	0.245	0.295

Table 5-4 Cross-Tabulation by Different Categories

Variable	Landless & No Schooling	Landless & Low Caste	Low Caste & No Schooling	Landless & No Schooling & Low Caste
VEP (based on each cross sectional data)	0.694	0.811	0.771	0.812
VEP_GLS (based on panel data)	0.658	0.847	0.805	0.836
POVERTY (static measure of poverty)	0.698	0.755	0.726	0.772
VEU	0.965	0.976	0.877	0.962
VEU_POVERTY	0.604	0.679	0.580	0.682
VEU_AGGREGATE	0.356	0.509	0.435	0.594
VEU_IDIOSYNCRATIC	0.331	-0.223	0.032	-0.171
VEU_UNEXPLAINED	-0.326	0.011	-0.170	-0.143

Variable	Small Farmers & No Schooling	Small Farmers & Low Caste	Small Farmers & No Schooling & Low Caste
VEP (based on each cross sectional data)	0.716	0.834	0.839
VEP_GLS (based on panel data)	0.721	0.896	0.884
POVERTY (static measure of poverty)	0.637	0.728	0.784
VEU	1.543	0.869	0.907
VEU_POVERTY	0.427	0.599	0.636
VEU_AGGREGATE	0.019	0.117	0.115
VEU_IDIOSYNCRATIC	1.365	0.373	0.523
VEU_UNEXPLAINED	-0.268	-0.221	-0.368

IV. Concluding Observations

Some important findings are summarized from a larger policy perspective.

An attempt was made to assess the vulnerability of rural households in the semi-arid tract of South India, based upon the ICRISAT panel survey. Both *ex ante* and *ex post* measures of vulnerability were computed. The latter were decomposed into aggregate and idiosyncratic risk, and poverty components. Our decomposition shows that idiosyncratic risks account for the largest share (37%), followed by poverty (35%) and aggregate risk (22%). It is somewhat surprising that idiosyncratic risks (e.g. illness or unemployment) contribute more than poverty to vulnerability. Despite some degree of risk-sharing at the village level, the landless or small farmers are vulnerable to idiosyncratic risks, forcing them to reduce consumption. Subsets comprising the landless without education or members of lower castes are highly vulnerable to idiosyncratic and aggregate risks.

An important conclusion that emerges from the empirical analysis is that, while poverty and vulnerability are related and overlap to some extent, these are distinct concepts and broaden the area of intervention. Deprivation must be viewed from a larger perspective that goes beyond poverty status in a specific year or month, allowing for frequent and large changes in income, sources of income, and prices, as a consequence of changes in the policy regime, natural disasters, conflicts, seasonality of agricultural production, personal misfortunes. If credit and insurance markets were complete and worked efficiently, the case for a shift in anti-poverty policies would be weak. A feature, however, of rural areas- especially in the semi-arid region- is that not only such markets are incomplete but also subject to imperfections. So a broader area of intervention is consistent with a deeper concern for poverty reduction. Briefly, careful attention must be given to combining income augmenting policies with those that not only reduce aggregate and idiosyncratic risks but also build resilience against them, as elaborated below.

Responses to risks are usually classified into: (i) risk reducing; (ii) risk mitigating; and (iii) risk coping. This classification must, however, be used with some caution because of overlapping categories. Income diversification at the household level, for example, could be interpreted both as a risk reducing and risk mitigating measure. Similarly, workfare could be viewed both as a risk mitigating and a risk coping measure. Finally, nothing is implied about the workability and/or effectiveness of these measures as these are context-specific. Do smallholders sell bullocks when a crop fails, or do they borrow more frequently or do they simply participate more in public works programmes depends largely on the context. A related issue is that, while some of the responses at different levels may be mutually reinforcing (e.g. income diversification, micro-finance and agricultural research and extension), others may undermine the role of some (e.g. social security may adversely affect precautionary savings, social assistance may erode informal networks of support, workfare may discourage job search and income diversification).

In conclusion, so while there is a case for broadening the area of intervention, it is far from obvious what the trade-offs are between income diversification, savings, and different forms of insurance. The challenge of poverty reduction lies therefore not so much in a standard menu of policies but a clearer and deeper understanding of the risks that vast segments of rural population are exposed to and in building their resilience against them.

References

- Baltagi , B (2005) *Econometric Analysis of Panel Data*, Chichester, England, John Wiley & Sons Ltd.
- Baulch, B. and J. Hoddinott (2000) “Economic Mobility and Poverty Dynamics in Developing Countries”, *Journal of Development Studies*, vol. 36.
- Chaudhuri, S., J. Jalan and A. Suryahadi (2002) “Assessing Household Vulnerability to Poverty from Cross-Sectional Data: A Methodology and Estimates from Indonesia”, Discussion Paper, Columbia University
- Chaudhuri, S. and C. Paxson (1994) ‘Consumption Smoothing and Income Seasonality in Rural India’, mimeo, Princeton University.
- Dercon, S. (2005) “ Risk, Insurance and Poverty”, in S. Dercon (ed.) *Insurance Against Poverty*, Oxford: Oxford University Press.
- Gaiha, R. and A.Deolalikar (1993) “Persistent, Expected and Innate Poverty: Estimates for Semi Arid Rural India, 1974-1984”, *Cambridge Journal of Economics*, vol.17, no.4.
- Gaiha, R. and K. Imai (2004) “Vulnerability, Persistence of Poverty and Shocks- Estimates for Semi-Arid Rural India”, *Oxford Development Studies*, Vol. 32(2), June, 2004, pp.261-281.
- Gaiha, R and G. Thapa (2005) “Risk, Vulnerability and Poverty in Asia and the Pacific Region”, draft, Rome: PI, IFAD
- Gautam, M, 1991, ‘Measurement Errors and Consumption Analysis, A Case on Indian Panel Data, mimeo., World Bank.
- Hoddinott, J., and A. Quisumbing (2003a) “Data Sources for Microeconomic Risk and Vulnerability Assessments”, Social Protection Discussion Paper Series No.0323, The World Bank
- Hoddinott, J., and A. Quisumbing (2003b) “Methods for Microeconomic Risk and Vulnerability Assessments”, Social Protection Discussion Paper Series No.0324, The World Bank
- Hulme, D., K. Moore and A. Shepherd (2001) “Chronic Poverty: Meaning and Analytical Frameworks” CPRC Working Paper No.2, Chronic Poverty Research Centre, University of Manchester.
- Imai, K (2003) “Employment Guarantee Scheme as a Social Safety Net-Poverty Dynamics and Poverty Alleviation”, Department of Economics Working Paper, Ref. 149, Mar 2003, Department of Economics, University of Oxford.

Jacoby, H. and E. Skoufias (1993) 'A Note on the 'Reliability' of ICRISAT Household Expenditure Data', mimeo.

Jacoby, H. and E. Skoufias (1997), "Risk, Financial Markets, and Human Capital in a Developing Country", *Review of Economic Studies*, July 1997; 64(3): 311-35.

Jacoby, H., and E. Skoufias (1998) 'Testing Theories of Consumption Behavior Using Information on Aggregate Shocks', *American Journal of Agricultural Economics*, 80., pp.1-14.

Kamanou, G. and J. Morduch (2002) "Measuring Vulnerability to Poverty", UNU-WIDER Discussion Paper, No. 2002/58.

Kochar, A. (1995) "Explaining Household Vulnerability to Idiosyncratic Income Shocks", *American Economic Review*. May 1995; 85(2): 159-64

Kochar, A. (1999) "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India", *Review of Economics and Statistics*. February 1999; 81(1): 50-61.

Ligon, E. (2005) "Targeting and Informal Insurance" in S. Dercon (ed.) *Insurance Against Poverty*, Oxford: Oxford University Press.

Ligon, E and L. Schechter (2003) "Measuring Vulnerability", *The Economic Journal*, 113(486), C95-C102.

Lim, Y. and R. M. Townsend, 1998, 'General Equilibrium Models of Financial Systems: Theory and Measurement in Village Economies', *Review of Economics Dynamics*, I, pp. 59-118.

Pritchett, L., A. Suryahadi and S. Sumarto (2001) "Quantifying Vulnerability to Poverty: A Proposed Measure Applied to Indonesia", draft.

Ravallion, M. and S. Chaudhuri, 1997 , 'Risk and Village India: Comment', *Econometrica*, 65 (1), pp.171-184, Jan.

Rosenzweig, M. R. and Wolpin, K.I. (1993) 'Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India', *Journal of Political Economy*, Vol. 101, No.2., pp.223-244.

Scandizzo, P., R. Gaiha and K. Imai (2004) 'Income Stabilisation through the Employment Guarantee Scheme in India', mimeo, University of Rome "Tor Vergata".

Scandizzo, P., Gaiha, R. and K. Imai (2005) "Option Values, Switches and Wages - An Analysis of the Employment Guarantee Scheme in India", presented at the conference "Social Protection for Chronic Poverty Risk, Needs, and Rights: Protecting What? How?" held by IDPM, University of Manchester, 23-24 February 2005.

Townsend, M. R. 1994, 'Risk and Insurance in Village India', *Econometrica*, 62 (3), pp.539-591, May.

Walker, T.S. and J.G. Ryan, 1990, *Village and Household Economies in India's Semi Arid Tropics*, Baltimore, MD: The Johns Hopkins University Press.

World Bank (2000) *World Development Report 2000/01: Attacking Poverty*, Washington D.C

Appendix 1: Characteristics of Study Regions and Villages

Region and Village					
Mahbubnagar		Sholapur		Akola	
Aurepalle	Dokur	Shirapur	Kalman	Kanzara	Kinkheda
<p>Rainfall unassured; pronounced rainfall uncertainty at sowing</p> <p>Red soil; marked soil heterogeneity</p> <p>Kharif, or rainy season, cropping</p> <p>Paddy, castor, local kharif sorghum, pearl millet, and pigeon pea</p> <p>Agricultural intensification around dug wells and tanks</p> <p>Neglect of dryland agriculture</p> <p>Harijans and caste rigidities; inequitable distribution of land ownership</p>		<p>Rainfall unassured; frequent crop failure</p> <p>Deep black soils in lowlands; shallower lighter soils in uplands</p> <p>Rabi, or post-rainy season, cropping</p> <p>Rabi sorghum</p> <p>Some dug wells</p> <p>Technologically stagnant</p> <p>Tenancy; dearth of bullocks; more equitable distribution of land</p>		<p>Rainfall assured</p> <p>Black soils; fairly homogeneous</p> <p>Kharif cropping</p> <p>Upland cotton, mung bean, and hybrid sorghum</p> <p>Limited irrigation sources in 1970s and early 1980s</p> <p>Sustained technical change in dryland agriculture</p> <p>More educated</p>	

Source: Walker and Ryan (1990)

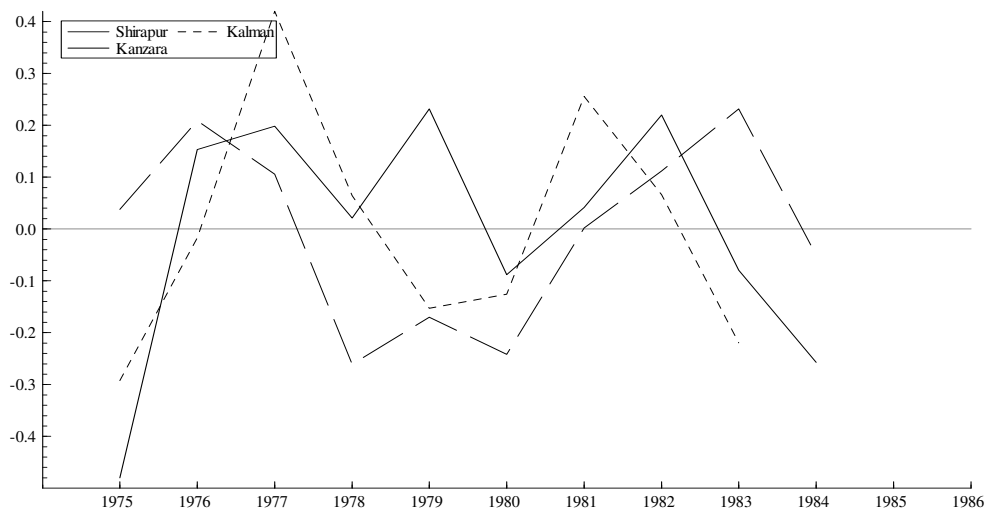
Appendix 2: Trend of Crop Shocks in Sample Villages

Figure 1: Crop Shock in Aurepalle and Dokur in Andhra Pradesh



Note: Crop Shock is averaged for each village.

Figure 2: Crop Shock in Shirapur, Kalman and Kanzara in Maharashtra



Note: Crop Shock is averaged for each village.

Source: Gaiha and Imai (2004)