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Measuring Vulnerability and Poverty

Estimates for Rural India

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Abstract

This paper measures the vulnerability of households in rural 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 risks and poverty components. Our decomposition shows that idiosyncratic risks account for the largest share, followed by poverty and aggregate risks. Despite some degree of risk-sharing, the landless or small farmers are vulnerable to idiosyncratic risks, forcing them to reduce consumption. Income-augmenting policies therefore must be combined with those that not only reduce aggregate and idiosyncratic risks but also build resilience against them.

Keywords: aggregate risks, idiosyncratic risks, poverty, vulnerability, semi-arid conditions

JEL classification: C21, C23, I32, C61

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Acronyms

FGLS	feasible generalized least squares
IV	instrumental variable
VLS	village level studies by CRISAT
SAT	semi-arid tracts
VEP	vulnerability as expected poverty
VEU	low expected utility
VER	exposure to risk

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1 Introduction

The objective of this study is to quantify 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'[1] in the sense that there exist those who are non-poor but vulnerable and those who are 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., the 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 wellbeing 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 (e.g., Hoddinott and Quisumbing 2003a, 2003b; Ligon 2005; Ligon and Schechter 2003; Gaiha and Imai 2004; 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 various risks—especially idiosyncratic—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 the 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 policymakers 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 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 Hoddinott 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 the resilience of subsets of households against such shocks can be anticipated. This is, of course, easier said than done. It is nevertheless arguable that, to the extent that ex post measures of vulnerability can be combined with ex ante measures, 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 panel household data for 1975-84. While several recent studies analyse vulnerability using the ICRISAT data, few have employed the various measures proposed and focus on identifying who the vulnerable are and

1 See, for example, Hoddinott and Quisumbing (2003a, 2003b), and World Bank (2000).

whether they are distinguishable from the poor in a static sense.[2] 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 2, 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 3 gives an exposition of three different empirical methodologies used here to measure vulnerability of households. Econometric results and findings are summarized in section 4. The final section offers concluding observations.

2 Data

2.1 Salient features

The analysis is based on (a subset) of the ICRISAT village level studies (VLS) datasets 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 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 six 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 ten 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 ten households was drawn from each tercile. Ten 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 under-represented in the sample. On average, across the six 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

2 Examples include Rosenzweig and Wolpin (1993), Chaudhuri and Paxson (1994), Townsend (1994), Ravallion and Chaudhuri (1997), Jacoby and Skoufias (1998), Lim and Townsend (1998), and Gaiha and Imai (2004).

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 socioeconomic characteristics of the 240 households in the sample villages representing three 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 five sample villages (excluding Kinkheda), as continuous data over the period 1975-84 are available only on this subset of households. This subsample is used to construct one measure of vulnerability i.e., vulnerability as expected poverty (VEP).[3] 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, namely Aurepalle, Shirapur and Kanzara, to derive estimates of VEU and VER measures.[4]

2.2 Risks and insurance in India

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

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

4 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 about own consumption of home production and grain stocks. 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. See Gautam (1991) for details of sources for the measurement errors.

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/gifts 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 markets (Kochar 1995, 1999), for example, have been reported. 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 summarized below.

i) Both poor and relatively affluent households are vulnerable to aggregate shocks such as crop shocks;

ii) The ability to cope with shocks is generally limited due to limited consumption insurance or risk sharing and credit constraints;

iii) 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;

iv) 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.

3 Methodology

Hoddinott and Quisumbing (2003a, 2003b) provide a comprehensive review of recent approaches and a ‘toolkit’ to quantify vulnerability of households and data requirements identifying the following three major approaches used in the empirical literature on vulnerability.[5]

3.1 Vulnerability as expected poverty (VEP)

VEP is an ex ante vulnerability measure, proposed by Chaudhuri, Jalan and Suryahadi (2002) who apply 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.

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

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, $c_{i,t+1}$, will be below the poverty line, z.[6]

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:

$$R_i(n, z) = 1 - \left[\left(1 - \left(\Pr(c_{i,t+1}) < z\right)\right), \ \ldots, \ \left(1 - \left(\Pr(c_{i,t+n}) < z\right)\right)\right] \tag{2}$$

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.[7]

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

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

$$V_{it} = \sum_s {}^S p_S \cdot P(c_{i,t+1}, z) = \sum_s {}^S p_s \cdot I[c_{i,t+1} \leq z] \cdot \left[(z - c_{i,t+1})/z\right]^\alpha \tag{1'}$$

where $\sum_s {}^S p_S$ 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

5 This section provides a summary of the methodological sections of Hoddinott and Quisumbing (2003b). See Hoddinott and Quisumbing (2003b) for more details.

6 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).

7 See, for example, Pritchett, Suryahadi and Sumarto (2000).

principle, this welfare weight could take values 0, 1, 2.[8] Aggregating across N households,[9]

$$\mathrm{VEP}_t = (1/N)\sum_i{}^N \sum_s{}^S p_S . I[c_{h,t+1} \le z].[(z - c_{h,t+1})/z]^\alpha \tag{4}$$

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:

$$\ln c_i = X_i \beta + e_i \tag{5}$$

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 coefficients of household characteristics, 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:

$$\sigma^2_{e,i} = X_i \theta \tag{6}$$

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:

$$E[\ln C_i | X_i] = X_i \hat{\beta} \tag{7}$$

$$V[\ln C_i | X_i] = X_i \hat{\theta} \tag{8}$$

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

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8 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.

9 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.

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

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 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 a good period 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 not large enough for estimating VEP measures. So we have included all households in the 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 intertemporal 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).

$$\ln Y_i = X_i'\beta_1 + L_i'\beta_2 + H_i'\beta_3 + e_i \tag{10}$$

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

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 FGLS.[10]

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

3.2 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). 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:

$$V_i = U_i(z_{ce}) - EU_i(c_i) \tag{12}$$

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

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

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.

$$\begin{aligned} V_i = & \left[U_i(z_{ce}) - U_i(E c_i)\right] && \text{(poverty)} \\ & + \left\{U_i(Ec_i) - EU_i\left[E\left(c_i \middle| x_t\right)\right]\right\} && \text{(covariate or aggregate risk)} \\ & + \left\{EU_i\left[E\left(c_i \middle| x_t\right)\right] - EU_i(c_i)\right\} && \text{(idiosyncratic risk)} \end{aligned} \tag{14}$$

where $E(c_i|x_t)$ is an expected value of consumption conditional on a vector of covariant variables, x_t.

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

$$\begin{aligned} VEU = (1/N)\sum_i^N & \left\{\left[U_i(z_{ce}) - U_i(Ec_i)\right] + \left\{U_i(Ec_i) - EU_i\left[E\left(c_i \middle| x_t\right)\right]\right\}\right. \\ & \left. + \left\{EU_i\left[E\left(c_i \middle| x_t\right)\right] - EU_i(c_i)\right\}\right. \end{aligned} \tag{15}$$

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 assumed.[11] The second is that the measurement is in terms of utility (i.e., utils).

Ligon and Schechter (2003) assume a particular form of utility function:

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

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

They assume:

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

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

$$c_{it} = X_{it}\beta_i + \eta_t + \alpha_i + v_{it} \tag{18}$$

where v_{it} is an error term which is also independent and identically distributed (~ IID (0, σ^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.

$$\begin{aligned}
V_i = & \left[U_i(E_c) - U_i(E\,c_{it})\right] && \text{(poverty)} \\
& + \left\{U_i(Ec_{it}) - EU_i\left[E(c_i|x_t)\right]\right\} && \text{(covariate or aggregate risk)} \\
& + \left\{EU_i\left[E(c_i|x_t)\right] - EU_i(c_i|x_t, x_{it})\right\} && \text{(idiosyncratic risk)} \\
& + \left\{EU_i\left[E(c_i|x_t, x_{it})\right] - EU_i(c_i)\right\} && \text{(unexplained risk and measurement error)}
\end{aligned} \tag{14′}$$

We can derive various conditional expectations in (14′) to decompose the entire vulnerability measure (or VEU measure) for each household by applying restricted least

[11] 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).

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 in (16) is problematic and idiosyncratic income risks in (14) may be insured. Consumption equation, as in (18), should have income on the right-hand side if the income data are available, as in our case. However, income, if used as the explanatory variable of consumption, 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 *typically* 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 normalized 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 per cent 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.

First stage:

$$y_{it} = X'_{it}\beta_1 + L'_{it}\beta_2 + H'_{it}\beta_3 + D'_t\beta_4 + \mu_i + e_{it} \tag{19}$$

Second stage:

$$c_{it} = \gamma_1 y_{it} + X'_{it}\gamma_2 + H'_{it}\gamma_3 + D'_t\gamma_4 + \alpha_i + v_{it} \tag{20}$$

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 instruments. 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 specification is chosen over fixed effects, following the Hausmann specification test. We then compute vulnerability by various conditional expectations of consumption, as in (14′).

3.3 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 VEP.

Consider a household, i, residing in a village, v, at time t. Let $\Delta \ln c_{itv}$ denote change in log consumption or the growth rate of consumption per capita of household i between t and t-1 and $S(i)_{tv}$ aggregate/covariate shocks and $S(i)_{itv}$ 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:

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

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.

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

Much of the empirical literature has concentrated on verifying whether β = 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 the vulnerability of consumption to income risk. In our specification we include schooling years of household head and their squares, caste, household size and their squares and the first differences 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 Quisumbing 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_{tv}, 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.

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

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).[12]

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

4 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 summarize vulnerability measures across different household groups, classified by landholding, educational attainment of household head and caste.

4.1 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 1-4. Results based on GLS panel data, where cross-sectional heteroscedasticity is modelled as in Equation (6), are shown in the last column of Table 4.

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

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12 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 (Gaiha and Imai 2004).

Table 1
Results for VEP (vulnerability as expected poverty) measure, 1975-77

	1975				1976				1977			
	Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i												
Age of household head	0.0135	(0.82)	-0.0151	(-0.20)	0.0149	(0.68)	0.0740	(0.89)	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)	-0.0007	(-0.78)	0.0000	(0.11)	0.0004	(0.41)
Household size	-0.1767	(-3.54)**	-0.3035	(-1.64)	-0.2606	(-4.50)**	-0.2096	(-1.12)	-0.2686	(-6.31)**	0.0506	(0.25)
Household size squared	0.0060	(1.75)+	0.0136	(1.15)	0.0117	(3.30)**	0.0112	(1.00)	0.0105	(3.98)**	-0.0010	(-0.09)
Caste dummies (high)	0.1909	(1.85)+	0.6303	(1.30)	0.3880	(2.65)**	-0.3037	(-0.57)	-0.0491	(-0.40)	0.3082	(0.53)
(middle high)	0.3610	(3.88)**	0.2954	(0.62)	0.4097	(2.96)**	-0.2134	(-0.42)	0.2630	(2.41)*	-0.1341	(-0.24)
(middle low)	0.1531	(1.57)	0.8427	(1.87)+	0.1167	(0.79)	0.3488	(0.71)	-0.0329	(-0.30)	0.0248	(0.05)
L_i												
Owned area of land	0.0848	(4.56)**	0.0102	(0.14)	0.0202	(0.73)	0.0398	(0.47)	0.0798	(4.30)**	-0.1109	(-1.22)
Owned area squared	-0.0016	(-2.48)*	-0.0002	(-0.08)	-0.0009	(-0.84)	0.0001	(0.04)	-0.0019	(-3.07)**	0.0016	(0.53)
Share of irrigated land	0.0037	(4.08)**	-0.0050	(-1.03)	0.0042	(2.66)**	-0.0012	(-0.21)	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	(1.06)	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	(-1.76)+	0.0000	(-1.00)	0.0000	(-1.28)
H_i												
Schooling yrs of household head	-0.0006	(-0.02)	0.2595	(2.16)*	0.0275	(0.61)	0.0484	(0.36)	0.0551	(1.56)	-0.0645	(-0.44)
Schooling yrs squared	0.0030	(1.80)+	-0.0283	(-2.46)*	-0.0028	(-0.56)	0.0029	(0.23)	-0.0045	(-1.12)	0.0079	(0.58)
constant	6.0888	(13.90)	-1.8822	(-1.03)	6.6271	(12.71)	-4.0175	(-2.04)	7.0189	(14.01)	-2.5422	(-1.12)
No. of observations	198		198		200		200		198		198	
F	21.74**		1.53		11.96**		0.63		16.31		0.45	
R squared	0.6245		0.1045		0.4695		0.0454		0.5551		0.0340	

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

Table 2
Results for VEP (vulnerability as expected poverty) measure, 1978-80

	1978				1979				1980			
	Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i												
Age of household head	0.0108	(0.54)	0.0172	(0.19)	0.0053	(0.27)	0.0303	(0.35)	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)	-0.0003	(-0.37)	-0.0002	(-0.84)	0.0012	(1.34)
Household size	-0.2135	(-4.47)**	0.0109	(0.05)	-0.2194	(-4.77)**	-0.3899	(-2.09)*	-0.0816	(-1.87)+	-0.0877	(-0.47)
Household size squared	0.0070	(2.33)*	0.0002	(0.01)	0.0076	2.82**	0.0150	(1.33)	0.0011	(0.47)	0.0016	(0.15)
Caste dummies (high)	0.1976	(1.61)	0.5528	(1.01)	0.3507	2.94**	0.5456	(1.07)	0.2084	(1.62)	-0.0990	(-0.18)
(middle high)	0.2552	(2.32)*	0.1801	(0.34)	0.2695	2.64**	-0.2810	(-0.56)	0.2052	(1.73)+	0.0626	(0.12)
(middle low)	0.2439	(2.21)*	0.3591	(0.71)	0.1069	(0.99)	0.0477	(0.10)	-0.0468	(-0.38)	0.1696	(0.34)
L_i												
Owned area of land	0.0519	(2.85)**	0.0155	(0.18)	0.0819	4.04**	0.0620	(0.70)	0.0203	(0.82)	-0.0486	(-0.56)
Owned area squared	-0.0009	(-1.78)+	-0.0014	(-0.50)	-0.0020	(-2.89)**	-0.0030	(-0.94)	-0.0003	(-0.32)	0.0015	(0.44)
Share of irrigated land	0.0068	(4.36)**	0.0042	(0.67)	0.0069	5.97**	-0.0001	(-0.02)	0.0038	(1.98)*	0.0136	(2.73)**
Non-land production assets	0.0001	(3.57)**	0.0000	(-0.26)	0.0000	2.78**	0.0001	(1.39)	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	(-1.85)+	0.0000	(-0.89)	0.0000	(-1.70)+
H_i												
Schooling yrs of household head	0.0239	(0.68)	-0.1193	(-0.87)	0.0285	(0.79)	-0.1661	(-1.25)	-0.0334	(-1.09)	-0.1071	(-0.80)
Schooling yrs squared	-0.0032	(-0.81)	0.0150	(1.16)	-0.0034	(-0.8)	0.0184	(1.47)	0.0018	(0.63)	0.0054	(0.42)
Constant	6.6375	(13.32)	-3.4747	(-1.56)	6.7105	(13.10)	-2.2948	(-1.02)	5.6488	(7.49)	-0.1237	(-0.05)
No. of observations	197		197		196		196		196		196	
F	24.25**		0.41		28.61**		1.31		4.50**		1.45	
R squared	0.6510		0.0400		0.6888		0.0922		0.2583		0.2182	

Note: ** indicates the coefficient is significant at 1% level;

* = significant at 5% level;

\+ = significant at 10% level.

Table 3
Results for VEP (vulnerability as expected poverty) measure, 1981-83

	1981				1982				1983			
	Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)		Variance (θ)	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i												
Age of household head	0.0466	(1.44)	-0.2015	(-2.27)*	0.0788	(2.75)**	-0.2454	(-2.23)*	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)**	0.0024	(2.37)*	-0.0003	(-1.59)	-0.0005	(-0.57)
Household size	-0.1218	(-3.45)**	0.2270	(1.47)	-0.1872	(-6.84)**	0.2534	(1.34)	-0.1334	(-4.58)**	0.1538	(1.08)
Household size squared	0.0026	(1.69)+	-0.0197	(-2.28)*	0.0059	(5.18)**	-0.0182	(-1.70)+	0.0023	(1.92)+	-0.0074	(-1.03)
Caste dummies (high)	0.0299	(0.24)	-0.2172	(-0.46)	0.2699	(2.46)*	-0.3503	(-0.62)	0.0542	(0.49)	0.1073	(0.21)
(middle high)	0.1070	(0.88)	-0.1174	(-0.26)	0.2664	(2.64)**	-0.7467	(-1.34)	0.2909	(2.52)*	0.3196	(0.63)
(middle low)	-0.1632	(-1.18)	0.5152	(1.15)	-0.0093	(-0.08)	-0.1218	(-0.23)	-0.0408	(-0.34)	0.6130	(1.24)
L_i												
Owned area of land	0.0482	(2.03)*	-0.0019	(-0.02)	0.0533	(2.68)**	-0.0888	(-0.88)	0.1132	(4.97)**	0.0072	(0.08)
Owned area squared	-0.0018	(-2.32)*	-0.0013	(-0.41)	-0.0020	(-2.01)*	0.0032	(0.85)	-0.0026	(-3.30)**	-0.0009	(-0.25)
Share of irrigated land	0.0055	(4.03)**	0.0014	(0.30)	0.0032	(3.51)**	-0.0066	(-1.23)	0.0042	(2.94)**	0.0018	(0.33)
Non-land production assets	0.0000	(4.13)**	0.0001	(2.10)*	0.0000	(4.99)**	0.0001	(2.54)*	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	(-2.09)*	0.0000	(1.63)	0.0000	(-0.99)
H_i												
Schooling yrs of household head	0.0267	(0.80)	-0.1195	(-1.03)	0.0526	(1.76)+	-0.2586	(-1.79)+	0.0539	(1.75)+	-0.0487	(-0.38)
Schooling yrs squared	-0.0036	(-0.98)	0.0071	(0.63)	-0.0037	(-1.00)	0.0206	(1.48)	-0.0025	(-0.78)	0.0014	(0.11)
Constant	5.4574	(6.33)	2.0132	(0.84)	5.0376	(6.73)	2.5040	(0.82)	6.1234	(9.34)	-4.6948	(-1.64)
No. of observations	197		197		197		197		198		198	
F	7.72**		1.81		22.89**		1.98		12.29**		0.51	
R squared	0.3726		0.1219		0.6378		0.1321		0.4846		0.0378	

Note: ** indicates the coefficient is significant at 1% level;

* = significant at 5% level;

+ = significant at 10% level.

Table 4
Results for VEP (vulnerability as expected poverty) measure, 1984 and panel estimation for 1976-84

	1984				GLS panel estimation	
	Log (income p. c.) (β)		Variance (θ)		Log (income p. c.) (β)	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i						
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)*
L_i						
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)**
H_i						
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: ** indicates the coefficient is significant at 1% level; * = significant at 5% level; + = significant at 10% level.
In 1984 the data are available for only three villages, Aurepalle, Shirapur and Kanzara;
Estimation results for variance in the case of panel regression are not provided by the programme.

Caste dummies have significant coefficients 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, 1980 and 1984) and GLS panel results. As expected, both the 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 has a positive and significant coefficient in 1982, but the value is small) and schooling years of household head and its square (e.g., the former has a positive and significant effect in 1975 and the latter has a negative and significant effect). 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 compare VEP measures with VEU measures across different groups of households later in this section.

4.2 Vulnerability as low expected utility (VEU)

Table 5 provides results of IV estimation for Equations (19) and (20). Since differences between coefficients of the fixed effects IV and the random effects specifications are *not* systematic at the 5 per cent level when using the Hausmann test, the random effects IV specification is preferred (Baltagi 2005). The first stage regression on the normalized household income yields results similar to the panel regression in Table 4 except that high caste dummy does not have a significant positive coefficient.[13] In the second stage, normalized 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 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 6 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 per cent less than the hypothetical situation without any risk or inequality in consumption. In other words, vulnerability so defined is high.

Of course, the results presume 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 per cent of total vulnerability), as the sum of aggregate 0.1671 (22 per cent) and idiosyncratic risks, 0.2750 (37 per cent), is very large. Indeed, it is even larger than the vulnerability associated with poverty, 0.2586 (35 per cent). This is in sharp contrast with Ligon and Schechter's (2003) finding where the corresponding risk component is 0.0279 (14 per cent of the total vulnerability), as the sum of the aggregate (0.0264; 13 per cent) and idiosyncratic risks, (0.0014; 1 per cent). The vulnerability associated with poverty is

[13] It is because significant coefficient of 'high caste' in the second stage in turn has affected the first stage in the iterative estimation.

Table 5
Results for VEU (vulnerability as expected low utility) measure
G2SLS random effects IV regression for panel data, 1975-84

Variable	First stage		Second state	
	Normalized hh income		Normalized hh income	
	Coeff. (β)	t-value	Coeff. (γ)	t-value
y_{it}				
Normalized 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)
1977	0.2848	(3.62)**	0.0937	(0.64)
1978	0.1692	(2.14)*	-0.2052	(-1.41)
1979	0.2704	(3.38)**	-0.1324	(-0.89)
1980	0.2136	(2.64)**	-0.1285	(-0.86)
1981	0.5263	(6.37)**	-0.1676	(-1.07)
1982	0.6914	(8.26)**	-0.8669	(-5.32)**
1983	0.8348	(9.79)**	-0.7004	(-4.08)**
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
Hausmann test for the choice				
between fixed effects IV model	Chi^2 =	19.57		
and random effects IV model	Prob>Chi^2 =	0.297		

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

also large in our case (0.2586; 35 per cent), much larger than that in Bulgaria, 0.1079 (31 per cent 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 per cent of the total risk (i.e., the sum of aggregate and idiosyncratic risks and unexplained risk and measurement errors);

ii) Aggregate risk is large except in Shirapur (58 per cent of total risk in Aurepalle, 5 per cent in Shirapur and 26 per cent in Kanzara); and

iii) Unexplained risk is large in all three villages (38 per cent of the total risk in Aurepalle, 88 per cent in Shirapur and 60 per cent in Kanzara).

These results are different for the following reasons:

i) We have used adjusted consumption data, corrected for measurement errors, while Ligon (2005) uses unadjusted data;

ii) Our specifications differ from Ligon's (2005);[14]

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 per cent in our case and 70 per cent 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 are not straightforward, our analysis suggests that vulnerability associated with idiosyncratic and aggregate shocks has a significant negative impact on a household's wellbeing. 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 timeseries means of various household characteristics to explore the determinants of vulnerability in Table 6. 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 the VEU measure of poverty is. 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 7). 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 by fitting it to those below the poverty cut off point.

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

Table 6
Decomposition of VEU (vulnerability as expected low utility) and its determinants
Regression of each vulnerability measure on timeseries means of household variables (between estimator)

	VEU		= Poverty (inequality)		+ Aggregate risk		+ Idiosyncratic risk		+ Unexpected risk	
Average value	0.7476		0.2586		0.1671		0.2750		0.0470	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i										
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)
L_i										
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)
H_i										
Schooling yrs of household 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	

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

Table 7
Determinants of VEP (vulnerability as expected poverty) measure and static poverty

	VEP				Poverty	
	(based on cross-sectional data)		(based on panel data		(statis binary variable)	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
X_i						
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)+
L_i						
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)
H_i						
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**
Hausmann test for the choice between random-effects model and fixed-effects model	$Chi^2(11)$	= 86.03**	$Chi^2(11)$	= 21.01**	N/A	
R squared	0.2799		0.5942		0.2488	(Pseudo R^2)

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

It is noted that determinants of poverty and those of VEP measures are quite similar. In particular, landholding 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.

4.3 Vulnerability as uninsured exposure to risk (VER)

The results for VER are presented in Table 8. We estimate Equations (21) and (22) by applying random-effects GLS[15] 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.

[15] The Hausmann test favours random effects over fixed effects in all cases in Table 4.

Table 8
Results for VER (vulnerability as uninsured exposure to risk)
GLS random effects, GLS for panel data, 1975-84

	Aurepalle				Shirapur				Kanzara			
	Case A		Case B		Case A		Case B		Case A		Case B	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	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 difference 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)
ΔHousehold 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)
ΔHousehold 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*	
Hausmann test for the choice between random & fixed-effects	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: Case A: village mean of log income used;

Case B: Crop shock measure used;

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

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 $\Delta(\overline{\ln y_{vy}})$) 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 periods, the consumption is well (or over) insured in these villages.

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, implying that the risk was shared among households during a crop shock in these two villages**.**

This raises the issue of 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.

4.4 Vulnerability across different groups

Tables 9 and 10 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 poverty is *related* to but *distinct* from vulnerability. So also are ex ante (VEP) and ex post measures (VEU) of vulnerability *related* but *distinct* concepts. Their correlations (i.e., 0.25 to 0.26) are not high but non-negligible.

Table 9
Descriptive statistics of vulnerability measure

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 10
Correlation matrix of vulnerability and other household characteristics

	VEP	VEP_GLS	POVERTY	VEU	VEU_POVERTY	VEU_AG~E	VEU_ID~C	VEU_UNEXPLAINED	school	ownarea	lowcast	midlcast	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			
midlcast	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

Table 11
Comparisons of vulnerability across different groups

	Land-holding status			
Variable	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
	Household head's years of schooling			
Variable	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	
	Caste			
Variable	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 12
Cross-tabulation by different categories

Variable	Landless and no schooling	Landless and low cast	Landless, no schooling and low cast
VEP (based on each cross sectional data)	0.694	0.811	0.771
VEP_GLS (based on panel data)	0.658	0.847	0.805
POVERTY (static measure of poverty)	0.698	0.755	0.726
VEU	0.965	0.976	0.877
VEU_POVERTY	0.604	0.679	0.580
VEU_AGGREGATE	0.356	0.509	0.435
VEU_IDIOSYNCRATIC	0.331	-0.223	0.032
VEU_UNEXPLAINED	-0.326	0.011	-0.170
	Small farmers and no schooling	Small farmers and low caste	Small farmers, no schooling and low cast
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

Tables 11 and 12 summarize means of various vulnerability measures by landholding class, household head’s schooling years and caste. Here are some observations.

– The landless or small farmers are more vulnerable than larger farmers. In particular, small farmers face large idiosyncratic consumption risk.

– 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.

– Households in lower castes are more vulnerable than those in higher/upper castes.

– If households are landless and at the same time without education or in low castes, they are highly vulnerable to aggregate shocks.

5 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 per cent), followed by poverty (35 per cent) and aggregate risk (22 per cent). 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 the latter broadens 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 and 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 are 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 they are context-specific. Whether smallholders sell bullocks when a crop fails, or borrow more frequently or 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, microfinance 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: John Wiley & Sons Ltd.

Baulch, B., and J. Hoddinott (2000). 'Economic Mobility and Poverty Dynamics in Developing Countries'. *Journal of Development Studies*, 36 (6): 1-24.

Chaudhuri, S., and C. Paxson (1994). 'Consumption Smoothing and Income Seasonality in Rural India'. Discussion Paper 173. Princeton: Princeton University.

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 0102-52. New York: Columbia University.

Dercon, S. (2005). 'Risk, Insurance and Poverty'. In S. Dercon (ed.), *Insurance Against Poverty*. Oxford: Oxford University Press for UNU-WIDER.

Gaiha, R., and A. Deolalikar (1993). 'Persistent, Expected and Innate Poverty: Estimates for Semi Arid Rural India, 1974-1984'. *Cambridge Journal of Economics*, 17 (4): 409-21.

Gaiha, R., and K. Imai (2004). 'Vulnerability, Persistence of Poverty, and Shocks-Estimates for Semi-Arid Rural India'. *Oxford Development Studies*, 32 (2): 261-81.

Gautam, M. (1991). 'Measurement Errors and Consumption Analysis: A Case on Indian Panel Data'. Washington, DC: World Bank. Mimeo.

Hoddinott, J., and A. Quisumbing (2003a). 'Data Sources for Microeconometric Risk and Vulnerability Assessments'. WB Social Protection Discussion Paper 0323. Washington, DC: World Bank.

Hoddinott, J., and A. Quisumbing (2003b). 'Methods for Microeconometric Risk and Vulnerability Assessments'. WB Social Protection Discussion Paper Series 0324. Washington, DC: World Bank.

Hulme, D., K. Moore, and A. Shepherd (2001). 'Chronic Poverty: Meaning and Analytical Frameworks'. CPRC Working Paper 2. Manchester: Chronic Poverty Research Centre, University of Manchester.

Jacoby, H., and E. Skoufias (1997). 'Risk, Financial Markets, and Human Capital in a Developing Country'. *Review of Economic Studies*, 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 (1):1-14.

Kamanou, G., and J. Morduch (2002). 'Measuring Vulnerability to Poverty'. UNU-WIDER Discussion Paper 2002/58. Helsinki: UNU-WIDER

Kochar, A. (1995). 'Explaining Household Vulnerability to Idiosyncratic Income Shocks'. *American Economic Review*, 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*, 81 (1): 50-61.

Ligon, E. (2005). 'Targeting and Informal Insurance'. In S. Dercon (ed.), *Insurance Against Poverty*. Oxford: Oxford University Press for UNU-WIDER.

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*, 1 (1):59-118.

Pritchett, L., A. Suryahadi, and S. Sumarto (2000). 'Quantifying Vulnerability to Poverty: A Proposed Measure Applied to Indonesia'. WB Policy Research Working Paper 2437. Washington, DC: World Bank.

Ravallion, M., and S. Chaudhuri (1997). 'Risk and Village India: Comment'. *Econometrica*,65 (1): 171-84.

Rosenzweig, M. R., and K. I. Wolpin (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*, 101 (2): 223-44.

Townsend, M. R. (1994). 'Risk and Insurance in Village India'. *Econometrica*, 62 (3): 539-91.

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

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

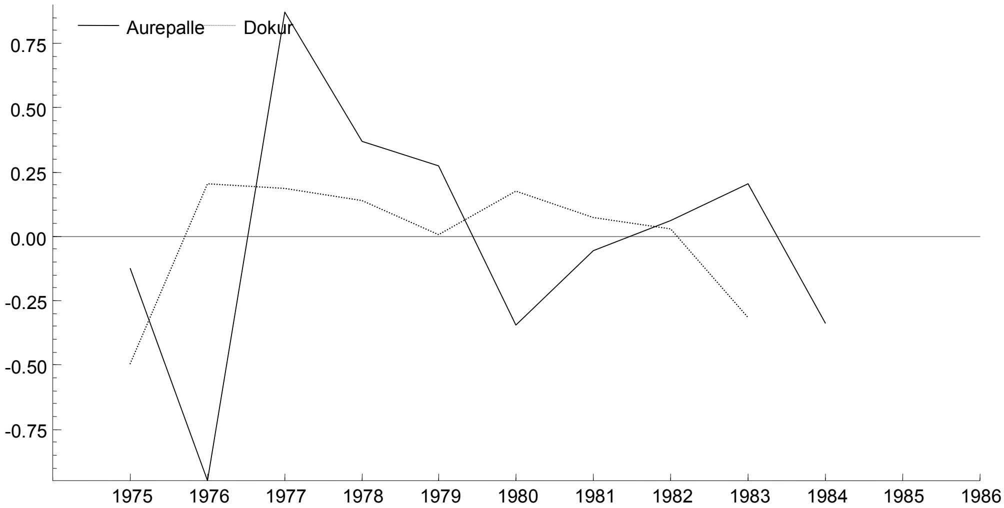
Appendix 1: Characteristics of study regions and villages

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

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 for Figures 1 and 2: Gaiha and Imai (2004)