Chapter 5

Poverty and Vulnerability in India and China

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Introduction

> "Reporting an 80-million drop in extreme poverty in the two years to 2004, the Bank said the improvement was entirely due to the rapid expansion in Asia's two most populous countries" (Guardian, 16 April 2007).

> "With an average annual growth rate of 10 percent, China has lifted over 600 million of its 1.3 billion citizens out of extreme poverty—those who earn less than $1 a day—since 1981. In the same time period, India's 6.2 percent average annual growth rate has brought an estimated 300 million of its 1.1 billion people out of extreme poverty…The World Bank estimates that the number of poor increased by at least 100 million as a result of the food and fuel crises" (Newsweek in November 2008).

The first quotation suggests that poverty reduction in India and China is important simply because of the large share of the poor in these two countries, in particular in India in the world's poor. Economic growth in these countries has driven the poverty reduction of the world in recent years. The graphs in Appendix 1 suggest that i) higher income growth has a close association with poverty reduction, ii) poverty reduction and income growth are higher in China than in India, and iii) higher income growth seems associated with higher income Gini. That is, while income growth led to the poverty reduction in absolute terms in China, the relatively rich benefited more in relative terms. The second quotation suggests the fragility of poverty reduction outcome as those above the poverty line would fall into poverty as a result of food and fuel crises. This signifies the importance of addressing vulnerability as opposed to poverty.

While it would be difficult to cover all the aspects of poverty in China and India, this paper focuses on a few important aspects to analyze poverty and India and China (Gaiha and Imai, 2009; Jha, Imai, and Gaiha, 2009; Imai, Wang, and Kang, 2009) drawing upon my research.

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Data

The analysis in Gaiha and Imai (2009) 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.

[1] The study is funded by Australian Research Council-AusAID Linkage grant LP0775444 and a small fund from the DFID and Chronic Poverty Research Centre in the UK under the DFID project on social protection and poverty led by Armando Barrientos, at Brooks World Poverty Institute (BWPI) of the University of Manchester. The views expressed are, however, are mine and do not necessarily represent the organisation to which I am affiliated.

Agroclimatologically, the SAT includes those tropical regions where rainfall exceeds potential evaporation four to six months a year (Walker and Ryan, 1990). The data collected are based on panel surveys conducted 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. 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).[2] However, given the 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) are problematic. We shall therefore use the expenditure data provided by Gautam (1991) for three villages, namely Aurepalle, Shirapur and Kanzara, to derive estimates of VEU and VER measures.[3]

Summary of the Results

Table 1 shows the decomposition of the VEU measure; 0.7476 in the head of the second column is our estimate of the vulnerability of all households. It is not necessarily easy to give it an intuitive interpretation, but this implies that the utility of the average household is 75 percent 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 areas 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 percent of total vulnerability), as the sum of aggregate 0.1671 (22 percent) and idiosyncratic risks, 0.2750 (37 percent), is very large. Indeed, it is even larger than the vulnerability associated with poverty, 0.2586 (35 percent). This is in sharp contrast with Ligon and Schechter's (2003) finding where the corresponding risk component is 0.0279 (14 percent of the total vulnerability), as the sum of the aggregate (0.0264; 13 percent) and idiosyncratic risks, (0.0014; 1 percent). The vulnerability associated with poverty is also large in our case (0.2586; 35 percent), much larger than that in Bulgaria, 0.1079 (31 percent 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 percent of the

[2] An exposition of different measures of vulnerability is given in a subsequent section.
[3] See Appendix 2 for the methodologies.

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 percent of total risk in Aurepalle, 5 percent in Shirapur and 26 percent in Kanzara).

iii. Unexplained risk is large in all three villages (38 percent of the total risk in Aurepalle, 88 percent in Shirapur and 60 percent 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);[4]

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 percent in our case and 70 percent 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.

Vulnerability as uninsured exposure to risk (VER)

The results for VER are presented in Table 2. We estimate Equations (A2-21) and (A2-22) by applying random-effects GLS[5] to the annual data for three sample villages, Aurepalle, Shirapur and Kanzara. The specification in Case A of each column is the same as that 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., β = 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, and that the risk was shared among households during a crop shock in these two villages**.** This raises the issue of why is VEU arising from idiosyncratic risks 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.

[4] 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.

[5] The Hausmann test favours random effects over fixed effects in all cases in Table 2.4.

Table 1 Decomposition of VEU (vulnerability as expected low utility) and its determinants: regression of each vulnerability measure on timeseries means of household variables (between estimator)

Average value	VEU 0.7476		=	Poverty (inequality) 0.2586		+	Aggregate risk 0.1671		+	Idiosyncratic risk 0.2750		+	Unexpected risk 0.0470	
	Coeff.	t-value		Coeff.	t-value		Coeff.	t-value		Coeff.	t-value		Coeff.	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 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.
Source: See text.

Table 2 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
Δln yit: 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)**
Δln yit: 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 Chi2 (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: Chi2(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.
Source: See text.

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.

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 percent), followed by poverty (35 percent) and aggregate risk (22 percent). 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.[6]

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 are such markets incomplete, but they 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

[6] A limitation of the present study is that our econometric results are based on panel data which are not so recent. However, as poverty rates are still high in backward states (e.g. Himanshu 2007) and in socially disadvantaged groups such as scheduled castes or tribes (e.g. Gaiha et al. 2008) - particularly in rural India - most of our findings are likely to have considerable validity for those state/regions and disadvantaged groups that have characteristics similar to those of the ICRISAT sample. The relatively small sample size is another limitation that has been partly overcome by using the panel data. While reliable panel data sets - especially for both rural and urban areas - are few and far between, the ICRISAT panel continues to be researched because of its richness. In any case, many of our results are robust to different specifications. The policy implications, however, could differ given the expansion of personal and weather insurance in rural areas in recent years and the expansion of job opportunities. Of particular significance is the two-year old National Rural Employment Guarantee Scheme. If implemented better, besides reducing the risk of poverty, it could serve the insurance function more effectively during periods of catastrophic events (e.g. droughts). So, while the disaggregation of vulnerability into the three components may change, it is far from self-evident that their ranking or relative shares would change significantly. We are grateful to an anonymous reviewer for raising this issue.

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 the rural population are exposed to and in building their resilience against them.

Public Works versus Food Subsidy in India

This section sheds empirical light on policy effects on public works and food subsidy based on Jha, Imai and Gaina (2009).

Due to the advantages arising from their salient features, such as self-targeting,[7]Rural Public Works (RPW) have been considered one of the best alternatives. However, the previous assessment of RPW pointed out that they did not reach the poor effectively (e.g. Gaiha et al., 2001). The past literature also suggests that poor workers do not have sufficient incentives to participate in the scheme through the poverty trap where those under the threshold will be either left out of the labour market (or unemployed) (e.g. Dasgupta, 1997) or receive only marginal wages as they cannot perform physically demanding tasks due to malnutrition or poor health. This would imply the difficulty in evaluating RPW on poverty as poverty or malnutrition are not necessarily their outcomes, but also affect the participation decision. The rigorous empirical work to examine the relationship between RPW and poverty is of enormous help in driving policy implications. The purpose of this paper is to statistically assess whether the participation in RPW affects poverty defined in consumption expenditure based on the National Sample Survey data in the 50th round in 1993-1994 and the 61st in 2004-2005, two rounds of the large national-scale household data. We use the data of participations in RPW for the 50th round and those on FFW (Food for Work) programme, a version of RPW, for the 61st round because of the data constraints.[8]

7 In self targeting, the participants themselves decide to participate in the scheme explicitly or implicitly by comparing the potential benefits (e.g. wage incomes, reduction of seasonality or risk) and costs (e.g. physical labour, transportation costs, opportunity costs). Better targeting performance through work requirements would lead to the better cost effectiveness of poverty interventions as put forward as ‘screening arguments’ by Besley and Coates (1992).

8 The data on RPW in the 50th round and those on FFW in the 61st round are the most reliable with relatively few missing observations,

As a comparison to RPW, this present study evaluated the poverty reducing effects of the Public Distribution System (PDS), the public scheme of food subsidy under which poor people are provided with basic food at subsidized price (e.g. rice, wheat, sugar, edible oil, soft cake and kerosene oil). While RPW has an advantage over PDS due to the nature of self-selection, PDS could be accessed by those who are unable to work (e.g. the elderly or the physically disabled). PDS is likely to have an impact on the nutritional conditions of household members because of its provision of food. However, there are relatively few systematic and rigorous studies to evaluate the impact of PDS on poverty.[9] [10]

However, evaluating the effects of RPW or PDS on poverty is not straightforward because of the endogeneity or the sample selection problem associated with access to these schemes. The participation in RPW is likely to be endogenous either because of the endogenous programme placement where policy makers purposefully allocate the fund according to the objectives of the programme (e.g. poverty alleviation in remote areas or disadvantaged groups) or the self-selection. The geographical placement of PDS may not be random, or could be endogenous.

This paper takes into account the endogeneity in assessing RPW in two ways. First, we employ the treatment-effects model, a version of the Heckman sample Selection Model (Heckman, 1979) where the participation equation is estimated and in the second stage poverty or consumption is estimated by the predicted participation among other determinants. Second, the propensity score matching (PSM) model is applied to statistically compare the poverty measures for those who have access to RPW and for those who do not and are matched by the propensity score derived by the probit or logit model where the characteristics of the households are taken into account.

The PSM first estimates the probit or logit model to estimate a function matching the proximity of one household to another in terms of household characteristics and then households are grouped to minimize the distance between matched cases. While it has some advantages over the IV (instrumental variable) model (e.g. not requiring the instrument or linearity as in the IV model), the sample selection bias would not be entirely corrected if there are important unobservable variables that would affect the household decision to participate in the programmes (e.g. health, intra-household bargaining, cultural or psychological factors which are not found in the data). The treatment-effects model also estimates the probit model with similar specifications to those in the first stage of PSM. In the second stage, the poverty measure is estimated by OLS while sample selection is corrected by using the estimates of probability of participating in the microfinance programmes. The model is fitted by a full maximum likelihood (Maddala, 1983). The merits of the

[9] An important exception is Bhalotra (2002) who analysed the effects of PDS on child nutrition. She found based on the household data collected by the National Council of Applied Economic Research (NCAER) in 1994 that (i) if the average subsidy for the average household on PDS is 23 percent, then the PDS-using household buys 23 percent more food and (ii) the additional expenditure on food translates into statistically significant increases of 0.09 standard deviations in height and 0.05 standard deviations in weight for boys, and into smaller increases for girls.

[10] See Bhalotra (2002, Table 2) for the importance of PDS and RPW in central plan budgetary expenditure in India where PDS had a share of 3.2 percent and rural employment programmes had 2.3 percent in 1997, the highest shares among other alternatives. This suggests that these are the two major programmes to support the rural poor in India.

treatment-effects model over PSM include that (i) the degree of sample selection is explicitly taken into account in the model and (ii) the determinants of the dependent variable in the second stage are identified. However, the treatment-effects model imposes strong distributional assumptions for the functions in both stages and the final results are highly sensitive to the choice of explanatory variables and the instrument. The presence of unobservable variables would also affect the results as in PSM. Given these limitations, applying different models would be useful as one model would serve to check the robustness of the results derived by another model.

The present study goes beyond the standard definition of poverty, which concerns the binary measure defined by the national poverty line based on income or consumption data. First, for the 50^{th} round, we use the data on malnutrition in terms of calories and proteins, which has been constructed by converting the detailed food expenditure data available in NSS 50-1.0 into their nutritional equivalents (Jha and Gaiha, 2003). That is, whether a household is poor is defined not only by the consumption, but also by nutritional deficiencies. This is important in light of the link between the labour market participation and nutrition, which leads to the nutrition-based poverty trap. Second, we have derived the vulnerability measures as the probability of a household falling into poverty using the cross-sectional estimation drawing upon Chaudhuri (2003) and Chaudhuri et al. (2002). While poverty and vulnerability are correlated, they are different as some households above the poverty threshold may be vulnerable, or those who are just below the poverty line but have secure income sources may not be vulnerable (e.g. Gaiha and Imai, 2009). Hence, the effects of RPW or PDS on poverty and those on vulnerability are likely to be different - given the high vulnerability in the backward areas, the policy role of reducing vulnerability or protecting households from vulnerable shocks is very important.

Summary of the Results

Vulnerability Estimates

Table 3 presents the regression results for vulnerability estimations for NSS 50 (1993-4) and NSS 61 (2004-5). The results for consumption (Equation (2)) or log mean per capita expenditure (MPCE) (Equation (3)) are reported. A few results are surprisingly contrary to the intuition. For example, in 1993, the coefficient estimate of the number of adult female members is negative and highly significant, that of being headed by a female member is *positive* and significant. Both are negative and significant in 2004. The proportion of adult members is positive and highly significant in 1993 and 2004, reflecting the negative effects of dependency burden on children and the elderly on per capita consumption. While the age of the household head is negative and significant to explain per capita household expenditure in 1993 with a significant non-linear effect suggested by the positive and significant coefficient estimate of its square, the signs are opposite in 2004. Higher levels of educational attainment are positively and significantly associated with higher per capita consumption in both 1993 and 2004. Dummy variables associated with larger areas of land owned are also positively associated with per capita expenditure in 1993 and 2004. Dummy variables on the household head's occupation show a similar pattern in the results for two rounds. Belonging to Schedule Castes (SC) or Schedule Tribes (ST) is negative and highly significant in 1993 and 2004. While the results of state dummies are omitted from the table, they indicate the high degree of geographical differences in household consumption in 1993 and 2004.

Table 3 Estimation of vulnerability equations

	NSS 50 (1993-1994)				NSS 61 (2004-2005)			
	Consumption log(MPCE)		Variance		Consumption log(MPCE)		Variance	
	Coef.	T	Coef.	t	Coef.	t	Coef.	t
Whether a household is headed by a female member	0.205	(24.15)**	0.439	(12.31)**	-0.021	(-3.67)**	0.230	(8.09)**
Number of adult female members	-0.325	(-98.54)**	-0.027	(-2.28)*	-0.123	(-51.36)**	-0.049	(-4.08)**
Number of adult male members	-0.261	(-89.61)**	0.061	(5.25)**	-0.101	(-43.24)**	-0.025	(-2.10)*
The proportion of adults in a household	2.177	(222.41)**	0.260	(6.05)**	0.627	(81.53)**	-0.063	(-1.62)
Age of household head	-1.010	(-10.19)**	-3.366	(-8.74)**	0.560	(7.52)**	-0.814	(-2.10)*
Age squared	1.052	(10.30)**	3.475	(8.67)**	-0.250	(-3.33)**	1.184	(3.05)**
The max. education of adult (Primary)	0.125	(20.15)**	0.078	(2.62)**	0.081	(18.09)**	-0.058	(-2.23)*
The max. education of adult (Middle)	0.211	(29.58)**	0.163	(5.14)**	0.197	(45.30)**	0.069	(2.85)**
The max. education of adult (>=Matriculates)	0.392	(51.19)**	0.309	(9.50)**	0.416	(74.64)**	0.328	(11.49)**
Land (0.1<=2.5 ha) (default: the landless)	0.129	(22.93)**	0.064	(2.43)*	0.051	(13.37)**	-0.048	(-2.37)*
Land (>2.5 ha) (default: the landless)	0.503	(8.11)**	0.298	(1.40)	0.273	(39.42)**	0.158	(4.49)**
Whether self-employed in non-agriculture	-0.076	(-8.60)**	-0.082	(-2.15)*	-0.118	(-21.33)**	-0.032	(-1.15)
Whether agricultural labour	-0.266	(-34.27)**	-0.299	(-8.73)**	-0.318	(-52.90)**	-0.329	(-10.33)**
Whether non-agricultural labour	-0.176	(-18.03)**	-0.207	(-4.58)**	-0.241	(-37.52)**	-0.201	(-5.99)**
Whether self-employed in agriculture	-0.078	(-10.13)**	-0.156	(-4.72)**	-0.129	(-24.63)**	-0.132	(-4.91)**
Whether a household belongs to SC (Scheduled Caste)	-0.178	(-27.18)**	-0.015	(-0.44)	-0.156	(-32.62)**	-0.088	(-3.17)**
Whether a household belongs to ST (Scheduled Tribe)	-0.116	(-23.60)**	-0.039	(-1.59)	-0.102	(-25.19)**	-0.092	(-4.04)**
Constant	8.833	(329.31)	-2.434	(-22.69)	9.741	(489.22)	-2.992	(-27.98)
Number of obs		58664		58664		78873		78873
F(31, 58632)		2610		41	F(51, 78821)	1065		45
Prob > F		0		0		0		0
Root MSE		0		2		0		2

** = significant at 1% level. * = significant at 5% level. + =s ignificant at 10% level.

Table 3 also shows the results of variance of log mean per capita expenditure. A female member's headedness of the household is positively and significantly associated with higher variance in consumption in 1993 and 2004, implying the wider range of (conditional) distribution of consumption for female headed households than for male headed households. Thus, the possibility is not precluded that some female headed households have very low consumption in 1993. A higher level of educational attainment of household members and larger land holding (more than 2.5 hectares) seems associated with higher consumption variance in both years. Not being agricultural labourers or not belonging to SC or ST is associated with higher variance of consumption. These estimation results are used to derive vulnerability measures.

Treatment-effects Model

Table 4 and Table 5 present the results of the treatment-effects model. Table 4 reports the regression results in the first stage whereby either the access to RPW or PDS is estimated by the probit model (for Equation (8)) and those in the second stage for the equation of poverty (or vulnerability or malnourishment) taking account of sample selection bias (for Equation (8)). Table 5 summarises the treatment effects for various cases. Four cases are highlighted in Tables 4 and 5, namely, Case 1 - the case where the treatment effect of RPW is estimated by the NSS 50th round in 1993; Case 2 - the case for PDS in 1993 or NSS 50; Case 3 - the case for RPW (where it is proxied by FFW, a version of RPW due to the data constraints) in 2004 or NSS 61; and Case 4 - the case for PDS in 2004 or NSS 61.

We briefly explain the determinants of participation in RPW and the access to PDS in 1993 and 2004. Female member headedness of the household is a negative and significant determinant of RPW participation in Cases 1 and 3 and a positive determinant of PDS access, which is significant in Case 4. The more female adult members, the more likely it is for a household to have access to PDS (Cases 2 and 4). The more male adult members would drive the household to participate in RPW in 1993 and 2004 and to access PDS in 2004. The dependency burden is positively and significantly associated with the PDS access, as suggested by the negative coefficient estimates for the share of adult members in the household. A household with an older head is more likely to have access to PDS in 1993 and 2004. Education dummies are negative and significant in most cases, which implies the household with lower levels of educational attainment or without literate members tends to access RPW and PDS. This is indirect evidence of good targeting performances of these schemes. The households with an owned land area from 0.1 to 2.5 hectares are more likely to participate in RPW than the landless or those with land larger than 2.5 hectares in 1993 and 2004 (Cases 1 and 3). Whilst the landless are more likely to have access to PDS than those with land in 1993 (Case 2), those with a land area from 0.1 to 2.5 hectares are more likely to access PDS than the rest in 2004 (Case 4). The agricultural or non-agricultural labourer tends to join RPW and PDS. The schemes are more likely to be utilised by those belonging to SCs or STs. While predicted male wage is positive and significant in 1993, it is negative and highly significant in 2004 in the RPW participation equation. The coefficient estimate of the food price index is positive and significant in the PDS equation.

Table 4 reports the results of the second-stage regressions where the dependent variable is (a) consumption-based poverty (in the first panel of the second stage results), (b) vulnerability estimate (in the second panel), and (c) malnutrition based on calorie and protein only for the NSS 50th round (in the third panel). We only summarise the key results. First, the coefficient of β_{λ}, the degree of sample selection, is significant in all the cases (most of which are negative as in Cases 1, 2, and 4 in (a) consumption-based poverty, in Cases 1 to 4 in (b) vulnerability, the first and the third columns of RPW for (c) nutrition-based poverty. The actual poverty reducing effects are affected by the sample selection effects and direct effects of the schemes, θ. The treatment effects are calculated and summarised in Table 5.

The comparison of determinants of (a) consumption-based poverty, (b) vulnerability estimate, and (c) malnutrition based on calorie and protein for the cases of RPW and PDS would be of empirical significance in itself. Overall, the determinants of poverty, vulnerability and malnutrition are similar with a few exceptions. Female member headedness is considered to be a factor of increasing the probability of being poor, but we observe a negative and significant coefficient estimate in Case 2 (NSS50) of consumption poverty, Case 1 (NSS50) of vulnerability, and Case 1 of calorie poverty and Case 2 of protein poverty for NSS50. Household composition is significantly associated with poverty, vulnerability and malnutrition. For example, they are negatively affected by the dependency burden or the number of adult female members in the household. A household with an older household head is more likely to be poor with some non-linear effect with the exception of Case 2 in (c), calorie based poverty which shows a positive sign. The higher levels of educational attainment and the larger land area tend to decrease the probability of being poor, vulnerable and malnourished. Belonging to SCs or STs is highly correlated with not only poverty, but also vulnerability and malnutrition.

Table 5 summarises the treatment effects associated with RPW and PDS. RPW decreases consumption-based and protein-based poverty significantly in 1993, but not calorie-based poverty as shown by Case 1. This might reflect the fact that RPW is sometimes physically demanding and requires calories to perform tasks. In 1993, significant *vulnerability* reducing effects are observed only for vulnerability that is calculated based on 80 percent of the national poverty line (and the effects are positive for 100 percent and 120 percent). In 2004, RPW is confirmed to have a significant impact on reducing poverty and vulnerability. On the contrary, PDS significantly *increased* consumption-based poverty and nutrition-based poverty in 1993 and consumption-based poverty in 2003 (Cases 2 and 4). However, PDS significantly *decreased* vulnerability in both 1993 and 2003. This may reflect the aspect of social protection in PDS.

We found significant and negative effects of the household participation in Rural Public Works and Food for Work Programmes on poverty, malnutrition (e.g. protein) and vulnerability in 1993 and 2004. However, once we apply the treatment-effects model separately for each state, a great degree of diversity is observed. Also, we do not find any significant results for RPW in pseudo panel data models.

On the contrary, the prevalence of poverty and malnutrition is significantly higher for households with access to PDS than those without. However, PDS has significant effects on reducing the vulnerability of households in 1993 and 2004, which has been confirmed by the treatment-effects model and PSM. The effects of PDS are different among different results. PDS decreased vulnerability based on 80 percent of the poverty threshold in the IV model applied to the pseudo panel.

Table 4 Treatment effects model (regression results)

1st Stage Probit	Case 1 NSS50 RPW Coef.	z		Case 2 NSS50 PDS Coef.	Z		Case 3 NSS61 RPW Coef.	z		Case 4 NSS61 PDS Coef.	z	
Whether a household is headed by a female member	-0.172	(-4.22)	**	0.034	(1.40)		-0.107	(-2.46)	*	0.039	(2.10)	*
Number of adult female members	-0.003	(-0.27)		0.056	(6.91)	**	0.022	(1.29)		0.105	(13.07)	**
Number of adult male members	0.047	(4.18)	**	0.009	(1.16)		0.080	(4.89)	**	0.039	(5.15)	**
The proportion of adults in a household	-0.053	(-1.21)		-0.192	(-6.37)	**	-0.091	(-1.68)	+	-0.375	(-15.28)	**
Age of household head	0.406	(1.04)		1.755	(6.42)	**	-0.663	(-1.24)		3.397	(13.90)	**
Age squared	-0.513	(-1.26)		-1.606	(-5.67)	**	0.614	(1.12)		-2.854	(-11.60)	**
The max. education of adult (Primary)	-0.091	(-2.87)	**	-0.022	(-1.10)		-0.065	(-2.13)	*	0.011	(0.63)	
The max. education of adult (Middle)	-0.094	(-2.73)	**	-0.046	(-2.06)	*	-0.211	(-6.77)	**	-0.062	(-3.91)	**
The max. education of adult (>=Matriculates)	-0.055	(-1.61)		-0.112	(-4.90)	**	-0.466	(-10.45)	**	-0.228	(-12.32)	**
Land (0.1<=2.5 ha) (default: the landless)	0.055	(2.05)	*	-0.158	(-8.56)	**	0.100	(3.71)	**	0.190	(14.29)	**
Land (>2.5 ha) (default: the landless)	-0.059	(-0.23)		-0.308	(-1.89)	+	-0.066	(-1.33)		-0.029	(-1.30)	
Whether self-employed in non-agriculture	-0.095	(-2.28)	*	0.070	(2.74)	**	0.496	(8.43)	**	0.206	(11.74)	**
Whether agricultural labour	0.093	(2.66)	**	0.102	(4.48)	**	1.023	(17.32)	**	0.350	(16.81)	**
Whether non-agricultural labour	0.247	(5.71)	**	0.200	(6.77)	**	1.112	(18.79)	**	0.268	(12.18)	**
Whether self-employed in agriculture	-0.082	(-2.37)	*	-0.067	(-2.99)	**	0.691	(12.41)	**	0.137	(7.95)	**
Whether a household belongs to SC (Scheduled Caste)	0.156	(5.15)	**	0.098	(4.50)	**	0.285	(9.50)	**	-0.015	(-0.82)	
Whether a household belongs to ST (Scheduled Tribe)	0.078	(3.13)	**	0.025	(1.41)		0.105	(3.53)	**	0.092	(5.92)	**
Predicted male wages (at NSS region)	0.002	(2.54)	*	-	-		-0.086	(-34.92)	**	-	-	
Food Price Index	-	-		0.061	(32.14)	**	-	-		0.156	(19.10)	**
Constant	-2.248	(-17.83)	**	-7.632	(-35.42)	**	0.643	(3.70)		-2.246	(-18.50)	
Number of obs		58664			58663			76686			78873	
LR chi2(52)		442		LR chi2(31)	13637		LR chi2(42)	5477			16624	
Prob > chi2		0			0			0			0	
Log likelihood		-9804			-24761			-7537			-36841	

2nd Stage (a)	Case 1 NSS50 RPW Coef.	z		Case 2 NSS50 PDS Coef.	Z		Case 3 NSS61 RPW Coef.	z		Case 4 NSS61 PDS Coef.	z	
poor (consumption)	poor (consumption)			poor (consumption)			poor (consumption)			poor (consumption)		
Whether a household is headed by a female member	-0.007	(-1.15)		-0.014	(-2.26)	*	0.010	(2.39)	*	0.011	(2.61)	**
Number of adult female members	0.010	(4.86)	**	0.011	(5.59)	**	0.055	(29.57)	**	0.058	(29.60)	**
Number of adult male members	0.022	(10.75)	**	0.024	(12.74)	**	0.037	(20.81)	**	0.039	(22.14)	**
The proportion of adults in a household	-0.026	(-3.44)	**	-0.034	(-4.51)	**	-0.306	(-52.01)	**	-0.318	(-49.50)	**
Age of household head	-0.511	(-7.79)	**	-0.441	(-6.78)	**	-0.164	(-2.79)	**	-0.036	(-0.56)	
Age squared	0.492	(7.23)	**	0.421	(6.28)	**	-0.024	(-0.40)		-0.131	(-2.11)	*
The max. education of adult (Primary)	-0.039	(-7.49)	**	-0.044	(-8.81)	**	-0.067	(-16.96)	**	-0.068	(-17.21)	**
The max. education of adult (Middle)	-0.059	(-10.49)	**	-0.065	(-12.00)	**	-0.129	(-34.52)	**	-0.135	(-36.14)	**
The max. education of adult (>=Matriculates)	-0.110	(-19.53)	**	-0.116	(-21.05)	**	-0.173	(-39.05)	**	-0.186	(-39.99)	**
Land (0.1<=2.5 ha) (default: the landless)	-0.032	(-6.97)	**	-0.034	(-7.29)	**	-0.031	(-9.90)	**	-0.021	(-6.39)	**
Land (>2.5 ha) (default: the landless)	-0.057	(-1.41)		-0.069	(-1.75)	+	-0.106	(-19.80)	**	-0.108	(-20.17)	**
Whether self-employed in non-agriculture	-0.003	(-0.51)		-0.005	(-0.84)		0.041	(9.78)	**	0.051	(11.51)	**
Whether agricultural labour	0.072	(12.02)	**	0.081	(13.77)	**	0.158	(31.53)	**	0.182	(33.29)	**
Whether non-agricultural labour	0.037	(4.39)	**	0.059	(7.37)	**	0.081	(14.93)	**	0.105	(19.12)	**
Whether self-employed in agriculture	-0.010	(-1.66)	+	-0.016	(-2.77)	**	0.017	(4.04)	**	0.027	(6.46)	**
Whether a household belongs to SC (Scheduled Caste)	0.106	(17.81)	**	0.118	(21.27)	**	0.106	(24.16)	**	0.108	(25.44)	**
Whether a household belongs to ST (Scheduled Tribe)	0.035	(7.97)	**	0.040	(9.36)	**	0.046	(13.35)	**	0.050	(14.17)	**
Θ	-0.595	(-5.81)	**	-0.115	(-3.39	**	0.275	(9.00)	**	-0.144	(-5.61)	**
β_λ	-0.261	(-5.65)	**	0.100	(5.20)	**	-0.097	(-6.52)	**	0.096	(6.52)	**
Constant	0.717	(7.00)		0.133	(7.42)		0.229	(14.04)		0.295	(14.51)	
Number of obs		58664			58663			76686			78873	
Wald chi2(103)	Wald chi2(62)	8662		Wald chi2(62)	15635		Wald chi2(103)	26299			33759	
Prob > chi2		0			0			0			0	

2nd Stage (b)	Case 1 NSS50 RPW Coef.	Z		Case 2 NSS50 PDS Coef.	Z		Case 1 NSS61 RPW Coef.	z		Case 2 NSS61 PDS Coef.	z	
	Vulnerability			Vulnerability			Vulnerability			Vulnerability		
Whether a household is headed by a female member	-0.126	(-28.69)	**	0.034	(1.40)		-0.002	(-0.86)		-0.003	(-1.51)	
Number of adult female members	0.147	(106.54)	**	0.056	(6.91)	**	0.050	(49.97)	**	0.048	(46.05)	**
Number of adult male members	0.119	(86.24)	**	0.009	(1.16)		0.040	(41.87)	**	0.040	(42.45)	**
The proportion of adults in a household	-1.418	(-276.53)	**	-0.192	(-6.37)	**	-0.221	(-69.10)	**	-0.212	(-61.86)	**
Age of household head	1.096	(24.45)	**	1.755	(6.42)	**	-0.100	(-3.10)	**	-0.172	(-5.07)	**
Age squared	-1.014	(-21.83)	**	-1.606	(-5.67)	**	-0.041	(-1.28)		0.023	(0.69)	
The max. education of adult (Primary)	-0.072	(-20.11)	**	-0.022	(-1.10)		-0.084	(-38.86)	**	-0.085	(-40.57)	**
The max. education of adult (Middle)	-0.142	(-36.66)	**	-0.046	(-2.06)	*	-0.130	(-63.92)	**	-0.131	(-66.07)	**
The max. education of adult (>=Matriculates)	-0.275	(-71.46)	**	-0.112	(-4.90)	**	-0.134	(-55.45)	**	-0.134	(-54.23)	**
Land (0.1<=2.5 ha) (default: the landless)	-0.074	(-23.67)	**	-0.158	(-8.56)	**	-0.030	(-17.76)	**	-0.031	(-17.24)	**
Land (>2.5 ha) (default: the landless)	-0.285	(-10.35)	**	-0.308	(-1.89)	+	-0.066	(-22.55)	**	-0.065	(-22.75)	**
Whether self-employed in non-agriculture	0.027	(5.96)	**	0.070	(2.74)	**	0.007	(3.17)	**	0.006	(2.38)	*
Whether agricultural labour	0.128	(31.06)	**	0.102	(4.48)	**	0.191	(69.90)	**	0.192	(66.01)	**
Whether non-agricultural labour	0.093	(15.98)	**	0.200	(6.77)	**	0.072	(24.26)	**	0.077	(26.48)	**
Whether self-employed in agriculture	0.030	(7.63)	**	-0.067	(-2.99)	**	0.011	(4.78)	**	0.012	(5.30)	**
Whether a household belongs to SC (Scheduled Caste)	0.099	(24.16)	**	0.098	(4.50)	**	0.121	(50.76)	**	0.123	(54.43)	**
Whether a household belongs to ST (Scheduled Tribe)	0.062	(20.39)	**	0.025	(1.41)		0.052	(27.33)	**	0.051	(27.40)	**
Θ	0.157	(1.93)	+	-0.014	(-2.68)	**	0.223	(14.19)	**	0.047	(3.44)	**
β_λ	-0.071	(-1.94)	**	-0.058	(-4.24)	**	-0.107	(-14.02)	**	-0.034	(-4.27)	**
Constant	0.405	(4.98)		-0.716	-1.42		0.139	(15.68)		0.119	(10.96)	
Number of obs		58664			58663			76687			78874	
Wald chi2(103)		131349			137687			65896.43			75524.38	
Prob > chi2		0			0			0			0	

** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

2nd Stage (c)	Case 1 NSS50 RPW Coef.	Z		Case 2 NSS50 PDS Coef.	Z		Case 1 NSS50 RPW Coef.	z		Case 2 NSS50 PDS Coef.	z	
	poor (calorie)			poor (calorie)			poor (protein)			poor (protein)		
Whether a household is headed by a female member	-0.016	(-2.59)	**	0.004	(1.77)	+	-0.007	(-1.13)		-0.012	(-2.28)	*
Number of adult female members	0.003	(1.78)	+	0.017	(9.19)	**	0.004	(2.35)	*	0.005	(2.50)	*
Number of adult male members	0.016	(8.12)	**	-0.011	(-1.52)		0.014	(7.68)	**	0.016	(9.33)	**
The proportion of adults in a household	-0.009	(-1.29)		-0.426	(-6.64)	**	-0.017	(-2.48)	*	-0.020	(-2.99)	**
Age of household head	-0.444	(-6.97)	**	0.402	(6.08)	**	-0.424	(-7.16)	**	-0.393	(-6.73)	**
Age squared	0.422	(6.39)	**	-0.048	(-9.76)	**	0.415	(6.76)	**	0.381	(6.34)	**
The max. education of adult (Primary)	-0.046	(-9.01)	**	-0.075	(-13.92)	**	-0.036	(-7.54)	**	-0.039	(-8.73)	**
The max. education of adult (Middle)	-0.072	(-13.11)	**	-0.124	(-22.83)	**	-0.053	(-10.42)	**	-0.057	(-11.72)	**
The max. education of adult (>=Matriculates)	-0.122	(-22.39)	**	-0.026	(-5.80)	**	-0.095	(-18.81)	**	-0.098	(-19.91)	**
Land (0.1<=2.5 ha) (default: the landless)	-0.028	(-6.20)	**	-0.128	(-3.30)	**	-0.021	(-5.02)	**	-0.019	(-4.70)	**
Land (>2.5 ha) (default: the landless)	-0.126	(-3.21)	**	-0.001	(-0.16)		-0.079	(-2.17)	*	-0.083	(-2.36)	*
Whether self-employed in non-agriculture	0.001	(0.18)		0.093	(16.13)	**	0.000	(0.03)		-0.003	(-0.49)	
Whether agricultural labour	0.090	(15.46)	**	0.057	(7.21)	**	0.072	(13.19)	**	0.076	(14.49)	**
Whether non-agricultural labour	0.048	(5.78)	**	-0.008	(-1.42)		0.032	(4.22)	**	0.046	(6.44)	**
Whether self-employed in agriculture	-0.005	(-0.94)		0.094	(17.08)	**	-0.004	(-0.74)		-0.008	(-1.56)	
Whether a household belongs to SC (Scheduled Caste)	0.088	(15.17)	**	0.050	(12.09)	**	0.081	(15.17)	**	0.090	(18.02)	**
Whether a household belongs to ST (Scheduled Tribe)	0.048	(11.23)	**	-0.008	(-0.22)		0.033	(8.28)	**	0.036	(9.56)	**
Θ	0.335	(2.97)	**	0.032	(1.68)	**	0.492	(5.16)	**	-0.025	(-0.82)	
β_{λ}	-0.145	(-2.86)	**	0.186	(10.50)	**	-0.216	(-5.02)	**	0.043	(2.47)	**
Constant	`	(4.47)	**				0.601	(6.30)		0.119	(7.37)	**
Number of obs		58664			58663			58664			58663	
Wald chi2(103)		8662.06			16730			8390.33			15405.5 7	
Prob > chi2		0			0			0			0	

** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 5 Treatment effects model (summary of the final results)
Policy effects on poverty and undernutrition

	NSS50	Effects on Poverty (Consumption Based)					
Case 1	RPW	Effects on Poverty					
	RPW	Effects on Poverty (Consumption Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	-0.00483	0.000964	-5.01**
	RPW	Effects on Poverty (Calorie Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	0.000821	0.001014	0.81
	RPW	Effects on Poverty (Protein Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	-0.00376	0.000864	-4.35**
Case 2	PDS	Effects on Poverty					
	PDS	Effects on Poverty (Consumption Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	0.077031	0.000832	92.62**
	PDS	Effects on Poverty (Calorie Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	0.054593	0.000925	58.99**
	PDS	Effects on Poverty (Protein Based)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	0.057819	0.00076	76.06**
	NSS61	Effects on Poverty (Consumption Based)					
Case 3	RPW						
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		2,290		76,709	-0.01565	0.001071	-14.61**
Case 4	PDS						
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		20,700		58,544	0.031625	0.000894	35.36*

Policy effects on vulnerability

	NSS50	Effects on Vulnerability					
Case 1	RPW	Effects on Vulnerability					
	RPW	Effects on Vulnerability (based on 100% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	0.004171	0.002312	1.804+
	RPW	Effects on Vulnerability (based on 80% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	-0.00641	0.002228	-2.879**
	RPW	Effects on Vulnerability (based on 120% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		3232		65947	-0.00641	0.002228	1.048
Case 2	PDS	Effects on Vulnerability					
	PDS	Effects on Vulnerability (based on 100% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	-0.0064	0.016	-2.5*
	PDS	Effects on Vulnerability (based on 80% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	-0.01357	0.002223	-6.104*
	PDS	Effects on Vulnerability (based on 80% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		17287		51917	-0.00112	0.002233	-0.503*
	NSS61	Effects on Vulnerability					
Case 3	RPW						
	PDS	Effects on Vulnerability (based on 100% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		2,290		76,709	-0.09649	0.001013	-95.29**
	PDS	Effects on Vulnerability (based on 80% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		2,290		76,709	-0.06807	0.000419	-162.32**
	PDS	Effects on Vulnerability (based on 120% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		2,290		-0.17155	0.001817	0.001013	-94.425**
Case 4	PDS	Effects on Vulnerability					
	PDS	Effects on Vulnerability (based on 100% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		20,700		58,544	-0.01436	0.000828	-17.357**
	PDS	Effects on Vulnerability (based on 80 % of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		20,700		58,544	-0.01576	0.001486	-10.61**
	PDS	Effects on Vulnerability (based on 120% of poverty line)					
	n.	treat.	n.	contr.	ATT	Std. Err.	t
		20,700		58,544	-0.01436	0.000828	-17.357**

Poverty and Vulnerability in China

Because the poverty and vulnerability issue is still being investigated by Imai, Wang, and Kang (2009), a brief summary of the results are given below. All the results are based on the Chinese Household Income Project (CHIP) in 1988, 1995 and 2002. CHIPs are based on surveys of around 8,000 rural households in about 20 provinces plus 7,000 urban households in 10-12 provinces, representative of the whole of China.

The disparity of rural-urban is the widest in the world. This is partly because of the double standard in the tax system for urban and rural areas. Rural residents have to pay agriculture tax simply because they live in a rural area and it is assumed they are involved in agricultural production although in many cases that is not true. Fees and charges by local governments sometimes exceed the agriculture tax several times.

While rural poverty declined in the period 1988-2002, it should be noted that poverty rates calculated based on income 'after tax' are much higher than 'before tax'. Table 7 shows that tax is regressive, though it is becoming less regressive in 2002. It should be noted that since 2004 the tax of special agricultural products has been cancelled except that on tobacco and that the agricultural tax was exempted in most provinces in 2005 and waived across the country in 2006.

Table 8 provides the estimation results for the first stage (income) and the second stage (variance) of VEP estimation. The results are generally intuitive. Particularly important in reducing vulnerability is education. Quantile regression is applied for the vulnerability to identify its determinants. This confirms the role of education in reducing vulnerability. Table 9 shows that not only poverty, but also vulnerability declined dramatically over the years.

Table 6 Poverty rate of rural China

	1988			**1995**		
	After tax	*Before tax1 (Land contract fee only paid)*	*Before tax2 (Assuming no land contract fee)*	After tax	*Before tax1 (Land contract fee only paid)*	*Before tax2 (Assuming no land contract fee)*
Lower Poverty line	15.1%	14.0%	12.7%	12.3%	10.5%	10.2%
Upper Poverty line	32.2%	30.6%	29.1%	28.1%	24.9%	24.1%

	2002		
	After tax	*Before tax1 (Land contract fee only paid)*	*Before tax2 (Assuming no land contract fee)*
Lower Poverty line	7.0%	5.9%	5.9%
Upper Poverty line	16.9%	15.1%	15.1%

Rural poverty line
Lower: 367 in 1988, 810 in 1995 and 876 in 2002
Upper: 525 in 1988, 1157 in 1995 and 1252 in 2002
Poverty lines for 1988 were estimated by deflating poverty lines of 2002 in Khan(2008) using rural CPI

Table 7 Average tax rate by household income decile

Income decile	1988	1995	2002	Income decile	1988	1995	2002
1 (Bottom 10%)	13.7	13.7	8.9	6	4.2	4.9	3.4
2	7.3	7.3	5.6	7	3.5	4.7	3.1
3	5.6	5.6	4.7	8	3.2	4	2.7
4	4.7	5.9	4.1	9	2.9	2.8	2.1
5	4.2	5.8	3.6	10	1.8	1.3	1.4

Table 8 Estimates for the measure of VEP

	1988		1995		2002	
	log (per capita Income)	Variance	log (per capita Income)	Variance	log (per capita Income)	Variance
Headage	0	-0.02	-0.008	-0.027	-0.021	0.003
	(0.07)	(1.52)	(1.77)*	(1.68)*	(4.34)***	(0.14)
Headage2	0	0	0	0.0003	0.0002	0
	(0.04)	(1.52)	(1.26)	(1.83)*	(3.54)***	(0.13)
Femalehead	-0.175	0.048	-0.19	0.105	-0.175	0.088
	(6.06)***	(0.37)	(4.49)***	(0.72)	(5.24)***	(0.74)
Married	0.002	-0.093	0.043	-0.066	0.036	-0.067
	(0.10)	(1.07)	(1.11)	(0.48)	(1.07)	(0.52)
Femaleshare	-0.202	-0.101	-0.174	-0.461	-0.127	0.164
	(5.93)***	(0.68)	(3.86)***	(2.73)***	(3.14)***	(1.04)
Depburden	-0.486	0.006	-0.513	-0.31	-0.599	0.036
	(16.94)***	(0.05)	(14.19)***	(2.23)**	(17.62)***	(0.27)
Ratio_Party	0.693	0.302	0.663	-0.071	0.554	0.224
	(11.25)***	(1.13)	(9.53)***	(0.30)	(11.09)***	(1.27)
Majority	0.052	-0.261	0.054	-0.188	0.029	0.02
	(2.32)**	(2.61)***	(1.92)*	(1.68)*	(1.30)	(0.24)
Elementary_Head	0.123	-0.022	0.032	-0.042	0.01	-0.17
	(7.26)***	(0.27)	(1.08)	(0.37)	(0.23)	(1.17)
Lowermiddle_Head	0.148	-0.099	0.107	0.001	0.079	-0.152
	(7.69)***	(1.12)	(3.41)***	(0.01)	(1.86)*	(1.03)
Uppermiddle_Head	0.167	0	0.183	-0.029	0.143	-0.235
	(6.82)***		(4.97)***	(0.21)	(3.24)***	(1.50)
Technical_Head	0.204	0.165	0.098	0.295	0.238	-0.165
	(3.86)***	(0.83)	(1.45)	(1.29)	(3.38)***	(0.77)
Higher_Head	0.157	0.061	0.36	-0.05	0.322	-0.282
	(1.38)	(0.14)	(3.78)***	(0.14)	(4.12)***	(0.98)
Land_farm	0	0.001	0	-0.003	-0.001	-0.01
	(0.54)	(2.48)**	(0.04)	(0.65)	(0.33)	(1.95)*
Ratio_Irrigated	0.1	-0.292	-0.041	0.22	0.057	-0.194
	(1.78)*	(1.15)	(0.49)	(0.72)	(0.64)	(0.65)
Ratio_Irrigated2	0.13	0.062	0.206	-0.285	0.008	0.013
	(2.31)**	(0.24)	(2.45)**	(0.93)	(0.09)	(0.04)
NorthEast	-0.179	0.79	0.282	0.117	0.05	0.213
	(6.28)***	(7.45)***	(8.88)***	(0.96)	(1.07)	(1.93)*
NorthCoast	-0.023	0.451	0.147	0.575	0.092	0.271
	(1.23)	(5.40)***	(5.94)***	(6.41)***	(3.71)***	(3.03)***
EastCoast	0.319	0.884	0.761	0.583	0.653	0.379
	(14.06)***	(9.25)***	(27.62)***	(5.51)***	(22.62)***	(3.94)***
SouthCoast	0.3	0.597	0.875	0.505	0.614	-0.033
	(12.27)***	(6.16)***	(25.02)***	(4.17)***	(21.01)***	(0.29)
MYRiver	-0.275	0.367	-0.115	0.12	-0.147	0.141
	(15.11)***	(4.41)***	(5.14)***	(1.30)	(6.37)***	(1.67)*
SouthWest	-0.04	0.264	-0.055	-0.145	-0.1	-0.307
	(2.27)**	(3.12)***	(2.45)**	(1.62)	(5.12)***	(3.64)***
NorthWest	-0.218	0.25	-0.322	0.192	-0.049	0.224
	(8.67)***	(2.01)**	(8.42)***	(1.24)	(1.34)	(2.10)**
Hilly	-0.019	-0.19	-0.15	0.257	-0.059	-0.093
	(1.39)	(3.06)***	(8.58)***	(3.80)***	(3.65)***	(1.47)
Mountainous	-0.075	-0.187	-0.307	0.127	-0.333	0.228
	(4.66)***	(2.59)***	(14.51)***	(1.57)	(17.82)***	(3.37)***
Electricity	0.176	0.163	0.169	0.429	0.325	0.426
	(11.14)***	(2.20)**	(3.77)***	(2.02)**	(3.57)***	(0.91)
Constant	6.336	-2.29	7.441	-2.125	8.027	-2.983
	-81.28	-6.96	-62.62	-4.68	-51.92	-4.37
Observations	9364	9364	7785	7785	9139	9139
R-squared	0.24	0.02	0.32	0.02	0.27	0.01
Joint Significance	F(26,9337) = 120.67	F(26,9337) = 8.73	F(26,7758) = 156.38	F(26,7758) = 5.00	F(26,9112) = 127.43	F(26,9112) = 5.32
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9 Poverty head count ratio and the VEP for rural China

		1988	1995	2002
Rural poverty	Lower poverty line	15.1%	12.3%	7.0%
	Upper poverty line	32.2%	28.1%	16.9%
The estimated rural VEP (with upper line)	High vulnerable $\hat{V}_i \geq 0.5$	2,207 households (23.6%)	1,287 (16.5%)	248 (2.7%)
	Low vulnerable $0.25 \leq \hat{V}_i < 0.5$	837 (8.9%)	510 (6.6%)	260 (2.8%)
	Non vulnerable $\hat{V}_i < 0.25$	6,320 (67.5%)	5,988 (76.9%)	8,631 (94.4%)

Rural poverty line Lower: 367 in 1988, 810 in 1995 and 876 in 2002
Upper: 525 in 1988, 1157 in 1995 and 1252 in 2002
Poverty lines for 1988 were estimated by deflating poverty lines of 2002 in Khan(2008) using rural CPI

Conclusion

The present paper first shows that poverty and vulnerability have reduced significantly in both India and China, although the rate of decline is much higher in China than in India. Second, geographical disparity of poverty and vulnerability is substantial in both India and China. Third, education, land, and social inequality are key factors in reducing a household's vulnerability in India. Fourth, conducting Rural Public Works (RPW) is an effective measure of the vulnerability reduction policy for China. Fifth, a large rural and urban gap has existed partly because of the regressive taxation and reversed welfare system in India, which had also impacted on vulnerability. However, the disparity declined in 2002 when the tax reform was being implemented. This has to be confirmed by more recent data.

While it would be difficult to make a comprehensive assessment of the issue, the present study suggests the importance of policy formulation in addressing vulnerability (e.g. through RPW, microfinance or social insurance policies).

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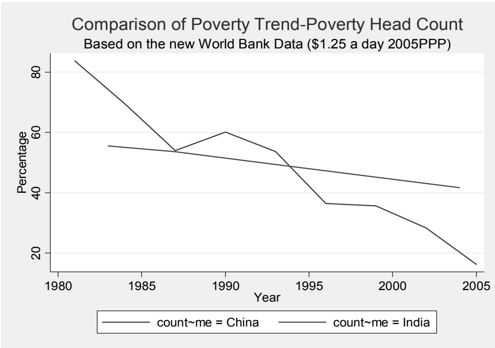
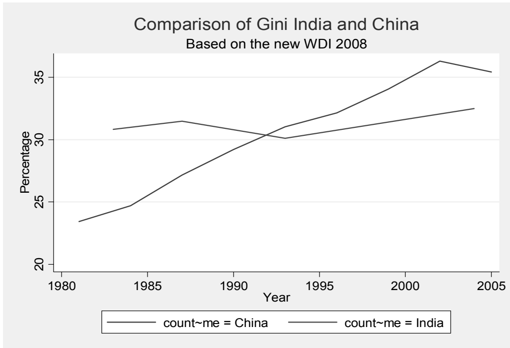
Appendix 1





Appendix 2 Methodology

Hoddinott and Quisumbing (2003a,b) provide a comprehensive review of recent approaches and a 'toolkit' to quantify the vulnerability of households and data requirements identifying the following three major approaches used in the empirical literature on vulnerability.[11]

Vulnerability as expected poverty (VEP)

VEP as an ex ante vulnerability measure, proposed by Chaudhuri *et al.* (2002), was applied by them 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.

$$V_{it} = \Pr\left(c_{i,t+1} \leq z\right) \qquad \text{(A2-1)}$$

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.[12]

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:

$$R_i(n, z) = 1 - \left[\left(1 - \left(\Pr\left(c_{i,t+1}\right) < z\right)\right), \ \ldots, \ \left(1 - \left(\Pr\left(c_{i,t+n}\right) < z\right)\right)\right] \qquad \text{(A2-2)}$$

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 the threshold probability, p.[13]

[11] This section provides a summary of the methodological sections of Hoddinott and Quisumbing (2003b). See Hoddinott and Quisumbing (2003b) for more details.
[12] The poverty cut-off point we use represents the minimum cost of a nutritionally adequate diet i.e., Rs180 per capita per year (at 1960-61 prices), which has been widely used in the literature; see Gaiha and Imai (2004) for more details.
[13] See, for example, Pritchett, Suryahadi and Sumarto (2000).

$$V_i(p, n, z) = I\{R_{it}(n, z) > p\} \qquad \text{(A2-3)}$$

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

$$V_{it} = \sum_s {}^S p_S \cdot P(c_{i,t+1}, z) = \sum_s {}^S p_s \cdot I[c_{i,t+1} \le z] \cdot \left[(z - c_{i,t+1})/z\right]^\alpha \qquad \text{(A2-1}'\text{)}$$

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 principle, this welfare weight could take values 0, 1, and 2.14 Aggregating across N households,[15]

$$VEP_t = (1/N)\sum_i {}^N \sum_s {}^S p_S . I[c_{h,t+1} \le z].[(z - c_{h,t+1})/z]^\alpha \qquad \text{(A2-4)}$$

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. Moreover, 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 *et al.* (2002). The consumption function is estimated as:

$$\ln c_i = X_i \beta + e_i \qquad \text{(A2-5)}$$

where c_i is the 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:

$$\sigma^2_{e,i} = X_i \theta \qquad \text{(A2-6)}$$

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:

$$E[\ln C_i | X_i] = X_i \hat{\beta} \qquad \text{(A2-7)}$$

$$V[\ln C_i | X_i] = X_i \hat{\theta} \qquad \text{(A2-8)}$$

[14] 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.

[15] 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.

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:

$$\hat{v}_i = \hat{\Pr}(\ln c_i < \ln z | X_i) = \Phi\left(\frac{\ln z - X_i\hat{\beta}}{\sqrt{X_i\hat{\theta}}}\right) \quad \text{(A2-9)}$$

This is an ex ante vulnerability measure that can be estimated by cross-sectional data. Equation (A2-9) provides 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 *et al.* 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 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).

$$\ln Y_i = X_i'\beta_1 + L_i'\beta_2 + H_i'\beta_3 + e_i \quad \text{(A2-10)}$$

$$\sigma^2_{e,i} = X_i'\theta_1 + L_i'\theta_2 + H_i'\theta_3 \quad \text{(A2-11)}$$

where i indexes the household. Y_i is the 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 the 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.[16]

Vulnerability as expected low utility (VEU)

There is a problematic or perverse feature of VEP. In case α > 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

[16] See Chaudhuri *et al.* (2002), and Hoddinott and Quisumbing (2003b) for technical details.

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:

$$V_i = U_i(z_{ce}) - EU_i(c_i) \tag{A2-12}$$

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

$$V_i = [U_i(z_{ce}) - U_i(Ec_i)] + [U_i(Ec_i) - EU_i(c_i)] \tag{A2-13}$$

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 faced by household h. The latter can be decomposed into aggregate or covariate and idiosyncratic risk, as shown below.

$$\begin{aligned} V_i = & \left[U_i(z_{ce}) - U_i(E\,c_i)\right] && \text{(poverty)} \\ & + \left\{U_i(Ec_i) - EU_i\left[E\left(c_i|x_t\right)\right]\right\} && \text{(covariate or aggregate risk)} \\ & + \left\{EU_i\left[E\left(c_i|x_t\right)\right] - EU_i(c_i)\right\} && \text{(idiosyncratic risk)} \end{aligned} \tag{A2-14}$$

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:

$$\begin{aligned} VEU = (1/N)\sum_i^N & \left\{\left[U_i(z_{ce}) - U_i(Ec_i)\right] + \left\{U_i(Ec_i) - EU_i\left[E\left(c_i|x_t\right)\right]\right\}\right. \\ & \left. + \left\{EU_i\left[E\left(c_i|x_t\right)\right] - EU_i(c_i)\right\}\right\} \end{aligned} \tag{A2-15}$$

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.[17] 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:

$$U(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{A2-16}$$

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

They assume:

[17] It is, however, arguable that, while the results may be sensitive to the functional form assumed, the relative components of the decomposition are unlikely to be affected much (Hoddinott and Quisumbing 2003b).

$$E(c_{it}|\overline{X}_t, X_{it}) = \alpha_i + \eta_t + X_{it}\beta \qquad \text{(A2-17)}$$

With the panel data, one can estimate α_i, unobservable time-invariant individual effects, η_t, time-effects the same across households and β, the effects of household characteristics or other observable factors on consumption. Using a two-way error component model (Baltagi 2005), Equation (17) can be estimated as:

$$c_{it} = X_{it}\beta_i + \eta_t + \alpha_i + v_{it} \qquad \text{(A2-18)}$$

where v_{it} is an error term which is 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.

$$\begin{aligned} V_i = & \left[U_i(E_c) - U_i(E\,c_{it})\right] && \text{(poverty)} \\ & + \left\{U_i(Ec_{it}) - EU_i\left[E(c_i|x_t)\right]\right\} && \text{(covariate or aggregate risk)} \qquad \text{(A2-14′)} \\ & + \left\{EU_i\left[E(c_i|x_t)\right] - EU_i(c_i|x_t, x_{it})\right\} && \text{(idiosyncratic risk)} \\ & + \left\{EU_i\left[E(c_i|x_t, x_{it})\right] - EU_i(c_i)\right\} && \text{(unexplained risk and measurement error)} \end{aligned}$$

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 in (16) is problematic and idiosyncratic income risks in (14) may be insured. The 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. Consequently, 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 percent 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 conducted in the same way as for VEP.

First stage:

$$y_{it} = X'_{it}\beta_1 + L'_{it}\beta_2 + H'_{it}\beta_3 + D'_t\beta_4 + \mu_i + e_{it} \qquad \text{(A2-19)}$$

Second stage:

$$c_{it} = \gamma_1 y_{it} + X'_{it}\gamma_2 + H'_{it}\gamma_3 + D'_t\gamma_4 + \alpha_i + v_{it} \qquad \text{(A2-20)}$$

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

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 a 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. Furthermore, 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:

$$\Delta \ln c_{itv} = \sum_i \lambda_i S_{tv} + \sum_i \beta_i S_{itv} + \sum_{tv} \delta_v (D_v) + \eta X_{itv} + \Delta\varepsilon_{itv} \qquad \text{(A2-21)}$$

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 the 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.

$$\Delta \ln c_{itv} = \alpha + \beta \ln y_{itv} + \gamma \Delta\left(\overline{\ln y_{vt}}\right) + \delta X_{itv} + \Delta\varepsilon_{itv} \qquad \text{(A2-22)}$$

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 the growth of consumption is related to the 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 the 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 the measures of vulnerability based on Equations (21) and (22) is the presumption that positive and negative income shocks have symmetrical effects. The 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* a household's own crop income. Village crop income (minus own crop income) at time t, C_{it}, is:

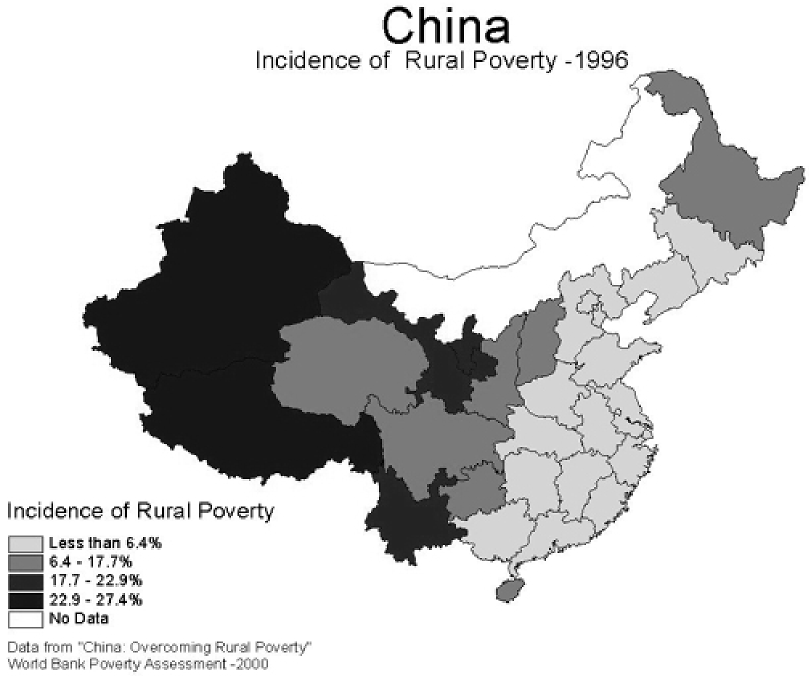
$$C_{it} = \sum_{j=1}^{n,\, j\neq i} c_{jt}$$

where c_{jt} is the 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.

$$\ln(C_{it}) = b_0 + b_1 T \qquad \text{(A2-23)}$$

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).[18] $S_{it} = \ln(C_{it}) - \ln(\hat{C}_{it})$ (24)

Appendix 3



[18] 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 2.1 and 2.2 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).

Appendix 4 Determinants of Vulnerability (VEP) in China (Quantile Regression Applied for Upper Poverty Line)

Determinants of VEP (with upper poverty line)

	1988					1995				
	10	*25*	*50*	*75*	*90*	*10*	*25*	*50*	*75*	*90*
Headage	**-0.003**	**-0.004**	-0.0005	**0.003**	**0.002**	-0.00004	0.00002	**0.002**	**0.005**	**0.009**
	(5.60)***	**(4.04)*****	(0.45)	**(1.84)***	**(1.75)***	(0.26)	(0.08)	**(3.06)*****	**(3.65)*****	**(5.27)*****
Headage2	**0.00003**	**0.00004**	0	-0.00002	-0.00002	0	0	**-0.00002**	**-0.00004**	**-0.00007**
	(5.23)***	**(3.74)*****	(0.81)	(1.39)	(1.61)	(1.14)	(0.57)	**(2.30)****	**(2.96)*****	**(4.11)*****
Femalehead	**-0.056**	**-0.099**	**-0.096**	**-0.082**	**-0.085**	**-0.003**	**-0.008**	**-0.036**	**-0.073**	**-0.096**
	(8.45)***	**(11.32)*****	**(7.97)*****	**(6.61)*****	**(5.57)*****	**(2.29)****	**(3.81)*****	**(5.83)*****	**(7.07)*****	**(5.67)*****
Married	**-0.023**	**-0.017**	-0.001	0.008	-0.002	**-0.012**	**-0.018**	**-0.025**	**-0.033**	-0.021
	(6.82)***	**(3.79)*****	(0.16)	(1.04)	(0.24)	**(6.23)*****	**(5.73)*****	**(4.62)*****	**(3.28)*****	(1.63)
Femaleshare	**0.105**	**0.154**	**0.131**	**0.14**	**0.16**	**0.011**	**0.017**	**0.033**	**0.062**	**0.126**
	(13.52)***	**(14.25)*****	**(10.63)*****	**(9.57)*****	**(11.59)*****	**(6.31)*****	**(5.48)*****	**(5.85)*****	**(5.25)*****	**(9.51)*****
Depburden	**0.261**	**0.406**	**0.337**	**0.345**	**0.417**	**0.036**	**0.059**	**0.145**	**0.242**	**0.428**
	(15.32)***	**(18.46)*****	**(17.63)*****	**(17.41)*****	**(21.78)*****	**(7.10)*****	**(7.68)*****	**(13.04)*****	**(11.35)*****	**(18.68)*****
Ratio_Party	**-0.314**	**-0.432**	**-0.304**	**-0.175**	**-0.061**	**-0.04**	**-0.047**	**-0.042**	**-0.034**	-0.018
	(14.50)***	**(13.37)*****	**(10.20)*****	**(5.91)*****	**(2.06)****	**(7.27)*****	**(5.67)*****	**(3.15)*****	**(2.73)*****	(1.00)
Majority	**-0.052**	**-0.077**	**-0.134**	**-0.1**	**-0.057**	**-0.012**	**-0.025**	**-0.072**	**-0.051**	**-0.041**
	(15.09)***	**(12.00)*****	**(9.86)*****	**(8.60)*****	**(5.94)*****	**(7.38)*****	**(5.54)*****	**(5.08)*****	**(4.56)*****	**(6.13)*****
Elementary_Head	**-0.077**	**-0.122**	**-0.105**	**-0.095**	**-0.095**	**-0.009**	**-0.017**	**-0.029**	**-0.015**	-0.008
	(15.79)***	**(15.52)*****	**(12.67)*****	**(9.62)*****	**(11.90)*****	**(7.18)*****	**(5.20)*****	**(6.26)*****	**(1.95)***	(0.58)
Lowermiddle_Head	**-0.089**	**-0.147**	**-0.125**	**-0.119**	**-0.127**	**-0.015**	**-0.028**	**-0.055**	**-0.063**	**-0.065**
	(14.86)***	**(16.53)*****	**(13.82)*****	**(10.20)*****	**(14.68)*****	**(7.83)*****	**(6.50)*****	**(9.97)*****	**(6.84)*****	**(4.79)*****
Uppermiddle_Head	**-0.086**	**-0.147**	**-0.129**	**-0.131**	**-0.163**	**-0.018**	**-0.033**	**-0.071**	**-0.091**	**-0.125**
	(15.00)***	**(14.61)*****	**(12.83)*****	**(10.83)*****	**(13.94)*****	**(7.80)*****	**(6.88)*****	**(10.88)*****	**(7.84)*****	**(8.36)*****
Technical_Head	**-0.025**	**-0.104**	**-0.127**	**-0.162**	**-0.213**	**0.003**	-0.006	**-0.025**	**-0.048**	**-0.065**
	(3.74)***	**(6.46)*****	**(6.17)*****	**(7.16)*****	**(9.90)*****	**(2.18)****	(1.47)	**(3.33)*****	**(3.68)*****	**(2.85)*****
Higher_Head	**0.13**	0.039	**0.058**	-0.00008	**-0.056**	**0.012**	0.006	**-0.034**	**-0.045**	-0.05
	(8.74)***	(1.13)	**(3.79)*****	(0)	**(2.80)*****	**(5.54)*****	(1.08)	**(2.67)*****	**(2.87)*****	(1.64)
Land_farm	**0.0003**	**0.0004**	**0.0003**	**0.0001**	0.00004	**0.0002**	**0.0004**	**0.0004**	-0.0004	**-0.002**
	(6.69)***	**(10.90)*****	**(4.99)*****	**(1.92)***	(0.89)	**(4.05)*****	**(3.74)*****	**(2.16)****	(1.12)	**(3.32)*****
Ratio_Irrigated	**-0.079**	**-0.19**	**-0.313**	**-0.513**	**-0.429**	**-0.003**	**-0.029**	**-0.122**	**-0.229**	**-0.217**
	(10.72)***	**(12.75)*****	**(15.45)*****	**(14.20)*****	**(13.63)*****	**(1.81)***	**(5.96)*****	**(9.31)*****	**(9.57)*****	**(6.50)*****
Ratio_Irrigated2	**-0.037**	**0.026**	**0.158**	**0.292**	**0.185**	**-0.011**	0.003	**0.057**	**0.107**	0.039
	(6.16)***	**(1.85)***	**(9.29)*****	**(10.21)*****	**(6.32)*****	**(5.42)*****	-0.89	**(5.16)*****	**(5.52)*****	(1.24)
NorthEast	**0.117**	**0.197**	**0.263**	**0.4**	**0.403**	**-0.018**	**-0.031**	**-0.062**	**-0.091**	**-0.142**
	(17.89)***	**(19.52)*****	**(13.57)*****	**(22.11)*****	**(28.92)*****	**(8.04)*****	**(8.80)*****	**(12.06)*****	**(10.39)*****	**(12.99)*****
NorthCoast	**0.02**	**0.04**	**0.037**	**0.034**	**0.031**	**-0.007**	**-0.005**	0.002	0.005	-0.008
	(11.74)***	**(9.10)*****	**(7.63)*****	**(4.27)*****	**(4.16)*****	**(6.77)*****	**(4.01)*****	(1.00)	(1.14)	(0.97)
EastCoast	**-0.061**	-0.005	**0.022**	**0.028**	**0.019**	**-0.021**	**-0.013**	0.002	0.005	-0.012
	(9.14)***	(0.76)	**(3.26)*****	**(3.49)*****	**(2.73)*****	**(6.28)*****	**(6.15)*****	(0.79)	(0.98)	(1.41)
SouthCoast	**-0.097**	**-0.064**	**-0.034**	**-0.02**	**-0.029**	**-0.037**	**-0.149**	-0.078	**-0.052**	**-0.048**
	(13.52)***	**(9.53)*****	**(5.31)*****	**(2.30)****	**(3.03)*****	**(7.06)*****	**(7.30)*****	(1.63)	**(5.41)*****	**(3.28)*****
MYRiver	**0.175**	**0.335**	**0.525**	**0.57**	**0.546**	**0.009**	**0.017**	**0.041**	**0.101**	**0.152**
	(16.58)***	**(22.51)*****	**(36.27)*****	**(43.17)*****	**(42.84)*****	**(6.80)*****	**(7.45)*****	**(10.34)*****	**(8.01)*****	**(12.41)*****
SouthWest	**0.022**	**0.035**	**0.048**	**0.103**	**0.133**	**0.008**	**0.021**	**0.069**	**0.126**	**0.099**
	(14.13)***	**(8.40)*****	**(8.62)*****	**(7.87)*****	**(6.99)*****	**(6.41)*****	**(9.54)*****	**(6.14)*****	**(8.80)*****	**(11.20)*****
NorthWest	**0.179**	**0.297**	**0.401**	**0.412**	**0.411**	**0.266**	**0.551**	**0.499**	**0.292**	**0.308**
	(17.03)***	**(16.42)*****	**(19.27)*****	**(24.05)*****	**(28.21)*****	**(7.37)*****	**(10.89)*****	**(23.57)*****	**(23.27)*****	**(19.62)*****
Hilly	**0.013**	**0.028**	**0.015**	-0.002	0.008	**0.01**	**0.017**	**0.036**	**0.059**	**0.103**
	(7.49)***	**(7.96)*****	**(3.45)*****	(0.44)	(1.61)	**(7.82)*****	**(9.83)*****	**(11.08)*****	**(9.63)*****	**(9.54)*****
Mountainous	**0.061**	**0.112**	**0.115**	**0.121**	**0.097**	**0.032**	**0.158**	**0.401**	**0.562**	**0.488**
	(15.22)***	**(15.73)*****	**(13.69)*****	**(14.16)*****	**(14.98)*****	**(6.41)*****	**(7.73)*****	**(18.70)*****	**(39.70)*****	**(36.51)*****
Electricity	**-0.113**	**-0.223**	**-0.299**	**-0.287**	**-0.286**	**-0.247**	**-0.484**	**-0.348**	**-0.129**	**-0.231**
	(14.12)***	**(14.87)*****	**(21.49)*****	**(26.11)*****	**(19.30)*****	**(4.44)*****	**(10.57)*****	**(17.17)*****	**(2.06)****	**(7.91)*****
Constant	0.215	0.371	0.483	0.482	0.541	0.27	0.531	0.426	0.183	0.207
	(14.58)***	(13.48)***	(15.05)***	(13.09)***	(14.53)***	(4.85)***	(11.38)***	(15.59)***	(2.60)***	(3.58)***
Observations	9364	9364	9364	9364	9364	7785	7785	7785	7785	7785
Joint	F(19,9337)	F(19,9337)	F(19,9337)	F(19,9337)	F(19,9337)	F(19,7758)	F(19,7758)	F(19,7758)	F(19,7758)	F(19,7758)
Significance	= 31.53	= 46.31	= 68.36	= 214.35	= 109.34	= 6.26	= 27.66	= 235.91	= 213.82	= 457.39
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.12	0.23	0.48	0.64	0.64	0.05	0.16	0.38	0.61	0.66

	2002				
	10	***25***	***50***	***75***	***90***
Headage	**-0.0000001**	**-0.0000007**	-0.000002	0	**-0.001**
	(2.84)*	**(1.92)***	(1.04)	(1.42)	**(1.88)***
Headage2	**0**	**1E-08**	0.0000003	**0.000001**	**0.00002**
	(3.51)*	**(2.47)***	(1.53)	**(1.84)***	**(2.07)***
Femalehead	0	0	0	0	0
	(1.52)	(1.55)	(0.91)	(0.27)	(0.54)
Married	**-0.000009**	0	-0.001	**-0.013**	**-0.042**
	(2.22)*	(1.60)	(1.44)	**(2.16)***	**(2.45)***
Femaleshare	**0.000001**	**0.000009**	**0.00002**	0	-0.001
	(3.78)*	**(3.57)***	**(3.06)***	(0.45)	(1.45)
Depburden	**0.00001**	**0.00004**	**0.0001**	**0.002**	**0.017**
	(4.23)*	**(4.46)***	**(3.49)***	**(3.33)***	**(3.77)***
Ratio_Party	**-0.000004**	**-0.00003**	**-0.00003**	**-0.0001**	-0.001
	(3.79)*	**(4.00)***	**(2.93)***	**(1.92)***	(1.30)
Majority	**-0.000003**	**-0.00004**	**-0.001**	**-0.007**	**-0.03**
	(5.19)*	**(1.67)***	**(2.59)***	**(2.45)***	**(2.29)***
Elementary_Head	0	-0.001	**-0.028**	**-0.105**	**-0.164**
	(1.10)	(1.34)	**(2.91)***	**(4.15)***	**(3.54)***
Lowermiddle_Head	0	-0.001	**-0.028**	**-0.106**	**-0.166**
	(1.16)	(1.34)	**(2.91)***	**(4.16)***	**(3.58)***
Uppermiddle_Head	0	-0.001	**-0.028**	**-0.106**	**-0.166**
	(1.16)	(1.34)	**(2.91)***	**(4.16)***	**(3.57)***
Technical_Head	0	-0.001	**-0.028**	**-0.106**	**-0.166**
	(1.00)	(1.33)	**(2.91)***	**(4.16)***	**(3.58)***
Higher_Head	0	-0.001	**-0.028**	**-0.105**	**-0.165**
	(0.61)	(1.30)	**(2.90)***	**(4.15)***	**(3.55)***
Land_farm	**0.000001**	**0.000001**	**0.000003**	**0.00003**	**0.0004**
	(4.26)*	**(4.19)***	**(3.03)***	**(2.83)***	**(3.92)***
Ratio_Irrigated	**-0.000002**	**-0.00002**	**-0.00003**	**-0.001**	**-0.011**
	(3.67)*	**(3.81)***	**(2.64)***	**(2.53)***	**(3.90)***
Ratio_Irrigated2	**0.000001**	**0.00001**	**0.00004**	**0.001**	**0.008**
	(2.60)*	**(3.17)***	**(2.20)***	**(2.22)***	**(3.62)***
NorthEast	**-0.00001**	**-0.00001**	**-0.00003**	**-0.0003**	**-0.004**
	(2.82)*	**(3.48)***	**(2.64)***	**(2.56)***	**(4.05)***
NorthCoast	0	**0.000001**	**0.000008**	**0.0001**	**0.001**
	(0.41)	**(1.91)***	**(2.41)***	**(2.63)***	**(1.89)***
EastCoast	**-0.00001**	0	0	**0.0001**	**0.001**
	(1.98)*	(1.50)	(0.34)	**(2.17)***	**(2.48)***
SouthCoast	**-0.00001**	**-0.001**	**0**	0	0
	(2.18)*	**(2.51)***	**(2.73)***	(1.54)	(1.48)
MYRiver	**0.000001**	**0.00001**	**0.00002**	**0.0003**	**0.002**
	(4.34)*	**(4.86)***	**(3.97)***	**(4.14)***	**(2.73)***
SouthWest	**0.000001**	**0.00001**	**0.00004**	**0.0004**	0.004
	(4.60)*	**(4.87)***	**(3.64)***	**(2.87)***	(0.96)
NorthWest	**0.000002**	**0.00002**	0	0	-0.001
	(4.86)*	**(3.53)***	(1.57)	(0.73)	(0.81)
Hilly	**0.000001**	**0.000004**	**0.00001**	**0.0001**	**0.001**
	(4.68)*	**(4.59)***	**(2.90)***	**(2.86)***	**(2.93)***
Mountainous	**0.00001**	**0.001**	**0.027**	**0.208**	**0.487**
	(2.18)*	**(2.56)***	**(8.82)***	**(14.92)***	**(28.00)***
Electricity	**-0.546**	**-0.595**	**-0.624**	**-0.548**	**-0.294**
	(13.47)*	**(18.04)***	**(13.92)***	**(10.12)***	**(9.71)***
Constant	0.546	0.596	0.654	0.674	0.556
	(13.47)***	(18.06)***	(14.34)***	(10.79)***	(9.45)***
Observations	9139	9139	9139	9139	9139
Joint	F(18,9112)	F(18,9112)	F(19,9112)	F(19,9112)	F(19,9112)
Significance	= 13.87	= 24.37	= 20.76	= 28.70	= 117.58
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.03	0.03	0.06	0.25	0.54

Absolute value of t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%