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Vulnerability to Downside Risk and Poverty in Vietnam

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Abstract

In this paper we propose a new measure of vulnerability called vulnerability to downside risk. The relevant benchmark for this new measure is the current level of wellbeing of a household as opposed to another benchmark such as the poverty line. We argue that this measure adds complementary information to existing measures such as Calvo and Dercon's (2007) axiomatic measure of vulnerability to poverty. We apply a measure of both vulnerability to downside risk and to poverty to data from Vietnam. We show that consumption smoothing capacities and the probability to experience an adverse event differ substantially between different wealth groups. Consequently, the relation between initial wealth and vulnerability to downside risk is highly non-linear. While moderately but not extremely poor households are relatively vulnerable to extreme poverty, they are less vulnerable to downside risk than any other group of households.

Key words: Vulnerability, Poverty, Shocks, Risk

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1 Introduction

The World Bank put the concept of vulnerability in the spotlight of poverty research by presenting it in the World Development Report 2000/01 as an important component of combating poverty. According to the report "vulnerability measures the resilience against a shock – the likelihood that a shock will result in a decline in well-being" (World Bank, 2001).

The reason for assigning such a prominent position to, as well as for increased economists' interest in vulnerability is threefold: *First*, threats faced by households – in combination with their (in-)capacity to smooth consumption and income – determine future levels of poverty. These levels are not fixed but change over time which underlines the crucial role of vulnerability in underlying hardship.[1] *Second*, vulnerability impacts negatively on the wellbeing of households. Expressed differently, not only current conditions such as levels of income and consumption matter for actual welfare, but also the risks a household faces (and the (in)ability to prevent, mitigate, and cope with these). *Third*, vulnerability is not only a dimension but also a cause of deprivation. For instance, poor households facing a risky future, i.e. vulnerability, are more likely to opt for stable, low-return sources of income than to invest in endeavours whose outcome is more uncertain. Though being a rationale choice, this behavior may trap households in poverty by rendering higher levels of income impossible. Therefore, attacking vulnerability has the potential to reduce poverty.

With this paper we intend to contribute to the concept and measurement of vulnerability. It has been widely acknowledged that respective measures have to focus on downside risk, i.e. on negative future outcomes (cf. Hoddinott and Quisumbing, 2003). Accordingly, Calvo and Dercon (2005) put forward an axiomatic measure of vulnerability to poverty and define every state of the world below the poverty line to be relevant. Also the concept of vulnerability as expected poverty (cf., for example, Pritchett *et al.*, 2000) uses this benchmark.

However, we argue that, when assessing future consumption shortfalls and their impact, it is also reasonable to regard every future scenario in which a household is below its current level of consumption (as opposed to the poverty line) as being relevant. For example, in terms of welfare consumption shortfalls above the poverty line are not automatically less important than the ones below it. This is the case if, for example, a huge consumption shortfall renders a formerly non-poor household

[1] Numerous analyses find that large proportions of the population move into and out of poverty over time, i.e. suffer from transient poverty (e.g. Gaiha and Deolalikar, 1993, Jalan and Ravallion, 1998, and Baulch and Hoddinott, 2000).

almost poor whereas a small consumption shortfall puts another household just below the poverty line. We present a *vulnerability to downside risk* measure which incorporates this argument and exclusively relies on vulnerability in the proper meaning of the word. That is, it focuses on downside risk regardless of households' expected poverty status and is only influenced by possible future outcomes which are below the current level of a household's wellbeing. While being different from Calvo and Dercon's (2005) concept of vulnerability to poverty in the choice of the relevant reference point, this new approach still belongs to "the class of measures where vulnerability is a probability weighted average of state-specific 'deprivation indices'..." (Calvo and Dercon, 2005).

With respect to the empirical estimation of vulnerability numerous attempts can be found in the literature. Some authors interpret the cross-sectional distribution of households' consumption as household specific distribution of possible future states of the world (e.g. Chaudhuri *et al.*, 2002). Ligon and Schechter (2003) propose a utility-based measure of vulnerability whose quantification is based on consumption variability obtained from panel data. Townsend (1994) and others regress consumption change on income change and take the coefficient of the latter as degree of risk exposure. In this paper we follow none of these attempts since – as discussed in greater detail below – they rely on very stringent assumptions, do not exclusively rely on downside risk, and/or do not consider the probability of possible future scenarios. Instead, we mimic Calvo and Dercon's (2007) empirical approach by determining relevant states of the world to which we assign probabilities and deprivation indices.

We compute a household specific measure of vulnerability to downside risk using a two wave panel from rural Vietnam. In order to compare it with other concepts of vulnerability we also estimate Calvo and Dercon's (2005 and 2007) measure of vulnerability to poverty. This allows us to shed light on the vulnerability of rural Vietnamese households from multiple angles.

The remainder of this paper is structured as follows: Section 2 provides background information on concepts and measures of vulnerability. In section 3 the new measure of vulnerability to downside risk and its properties are discussed. In section 4 vulnerability to downside risk and to poverty in three rural provinces in Vietnam is computed and the results are analyzed. Finally, in the last section the findings of the paper are summarized and conclusions drawn.

2 Concepts and measures of vulnerability

The crucial "ingredient" of vulnerability research is risk which plays a key role in economic development. Before elaborating on this, it is useful to define what we are talking about: Although technically risk does not have to have a negative connotation, in common practice such a meaning is typically attached to it. Harding (1998) defines risk as "a combination of the probability, or frequency, of occurrence of a defined hazard and the magnitude of the consequences of the occurrence: how often is a particular potentially harmful event going to occur, [and] what are the consequences of this occurrence?" In this paper we will follow this definition: Risk is a negative future event whose occurrence has a certain probability.

Among economists it is widely acknowledged that a household's level of wellbeing is not only determined by its current status in terms of, for instance, income, consumption, education and health, but also by the risks it faces (cf. Ligon and Schechter, 2004). Having a certain income but fearing to lose the job does not feel as good as having the same income and a safe employment. Therefore, risk is an important component in the analysis of wellbeing.

Risk not only impacts on wellbeing but also influences behavior and decision making processes (cf., for instance, Gunning and Elbers, 2003, and Dercon, 2007). People exposed to risk apply risk management strategies in order to prevent them from happening (for example, by building a dam to protect the belongings against a flood), mitigate their impact (for example, by contracting insurance) and / or cope with them as soon as they occur (for example, by migrating in order to find a new job). In absence of functioning credit and insurance markets such a behavior possibly results in lower growth, as well as high and persistent poverty rates. Imagine, for instance, a currently poor household which faces two possibilities: either it plants a type of crop that will yield a certain but low return, or it opts for a type that possibly offers a much higher return but is also much more prone to weather shocks and thus to an even lower return. Assuming risk aversion and the absence of a functioning insurance market this household is likely to choose the former possibility at the expense of remaining poor due to a constantly low source of income. On an aggregated level such a behavior hampers economic growth.[2] Therefore, risk is to be considered in the fight against poverty and the design of growth supporting policies.

[2] For empirical proof that risk management strategies can impact negatively on overall growth see, for example, Gunning and Elbers (2003).

Within the framework of vulnerability risk is commonly merged with (future) poverty. However, vulnerability (and even of vulnerability to poverty) is distinct from poverty. Non-poor households may face a risky future possibly pushing them below the poverty line. In Indonesia, for instance, the population share of the poor was rather low before the financial crisis took place during the second half of the 1990s. However, due to the crisis the share of the poor rose dramatically revealing that prior to the crisis numerous Indonesian households were non-poor but vulnerable to poverty (cf. Gaiha and Imai, 2009). Hence, when targeting policies to combat poverty it is important to identify not only the poor but also the part of the population which is at risk of becoming poor. Also, the required type of policy intervention may differ between poor and vulnerable beneficiaries. On the one hand, the creation of new sources of income might be the right "medicine" for the poor. On the other hand, the non-poor but vulnerable part of the population might rather be in need of insurance for their existing sources of income. Since standard poverty measures are not able to adequately identify the vulnerable part of the population researchers increasingly propose and discuss different measures of vulnerability.[3]

They can broadly be grouped into the following four categories: (i) vulnerability as expected poverty (VEP; cf., for example, Pritchett *et al.*, 2000, Chaudhuri *et al.*, 2002, and Kamanou and Morduch, 2004), (ii) vulnerability as low expected utility (VEU; cf. Ligon and Schechter, 2003), (iii) vulnerability as uninsured exposure to risk (VER; cf., for example, Townsend, 1994, and Amin, Rai and Topa, 2003), and (iv) vulnerability to poverty (Calvo and Dercon, 2007).

VEP measures the probability that a household will be below a pre-determined poverty line in the future. Expressed differently, this approach uses a benchmark – the poverty line z – and sets the probability that household h's consumption level in the future ($c_{h,t+1}$) will be below this benchmark equal to its actual degree of vulnerability:

$$VEP_{ht} = \Pr\,(c_{h,t+1} \leq z). \tag{1}$$

By doing so the concept differs from the one put forward by the World Bank (cf. chapter 1). Certainly, it incorporates the resilience against shocks – but only against the shocks that push a household below the poverty line or keep it there. Instead, expected consumption shortfalls above the poverty line are not considered – even if they are much more pronounced than the former ones.

[3] For a detailed discussion of different approaches to vulnerability see Hoddinott and Quisumbing, 2003.

VEP as presented in equation 1 does not account for risk sensitivity: Households are said to exhibit the same degree of vulnerability if they have the same expected outcome. However, uncertainty is likely to have a negative impact on wellbeing wherefore a household which will certainly receive the expected outcome should be less vulnerable than households facing different possible future outcomes. The severity of expected poverty is not considered, either. That is, a household with a 50% probability of being little below the poverty line has the same vulnerability as a household with a 50% probability of being far below the poverty line.

These shortcomings can easily be addressed by combining VEP with the Foster-Greer-Thorbecke (FGT; 1984) measures of poverty (cf. Hoddinott and Quisumbing, 2003). Assuming that $\sum_{i=1}^{N_h} p_{hi}$ reflects the sum of probabilities of all possible future scenarios faced by household h and $I_{hi}(\cdot)$ represents an indicator which equals one if $c_{hi,\,t+1} \leq z$ and zero otherwise equation 1 can be transformed into:

(2) $$VEP_{ht} = \sum_{i=1}^{N_h} p_{hi} \times I_{hi}(c_{hi,\,t+1} \leq z) \times \left(\frac{z - c_{hi,t+1}}{z}\right)^{\alpha}$$

Here, α captures risk attitudes and the type of poverty which is measured: households are risk averse if $\alpha > 1$, risk neutral if $\alpha = 1$, and risk proclivous if $0 < \alpha < 1$. Also, $\alpha = 0$ provides the expected poverty headcount, $\alpha = 1$ the expected poverty gap, and $\alpha > 1$ the expected severity of poverty.

Nonetheless, VEP based on FGT measures integrates households' risk attitudes only imperfectly: First, $\alpha > 1$ implies that absolute risk aversion is positively correlated with consumption (or any other measure of welfare; cf. Hoddinott and Quisumbing, 2003).[4] In the light of empirical findings regarding this matter such a property of risk attitude is highly unlikely (for an early example see Binswanger, 1981). Second, cases are possible in which VEP of a household decreases when moving from a certain consumption level just below the poverty line to an expected consumption level equal to the certain one but based on outcomes above and below it (for an example see Hoddinott and Quisumbing, 2003).

VEU – proposed by Ligon and Schechter (2003) – redresses this weakness. As opposed to VEP, this concept puts "expected utility" at the core of its analysis. It sets the vulnerability of household h (VEU_h) equal to the difference between the household's utility derived from certainty-equivalent consumption (z_{CE}) and the household's expected utility derived from its consumption (c_h):

[4] In case of FGT measures absolute risk aversion is given by (α –1)z/(z-c) (cf. Hoddinott and Quisumbing, 2003).

(3) $$VEU_h = U_h(z_{CE}) - EU_h(c_h)$$

By assuming U_h to be a weakly concave, strictly increasing function VEU accounts for risk preferences and is thus suited for quantifying the welfare loss provoked by risk. Another useful feature of VEU is that vulnerability can be decomposed into a poverty-, a covariate risk-, and an idiosyncratic risk-component as shown in equation 4 (cf. Ligon and Schechter, 2003):

(4) $$VEU_h = [U_h(z_{CE}) - U_h(Ec_h)]$$ (poverty component)

$$+\{U_h(Ec_h) - EU_h[E(c_h|x_t)]\}$$ (covariate risk-component)

$$+\{EU_h[E(c_h|x_t)] - EU_h(c_h)\}$$ (idiosyncratic risk-component)

where $E(c_h|x_t)$ equals the expected value of consumption given a vector of covariant variables x_t.

However, these advantages come at the cost of allowing possible positive outcomes to compensate for the vulnerability increasing effect of possible negative outcomes. Such a property is not desirable because a household might be labeled “non vulnerable” although in at least one possible future state of the world it faces severe destitution. Also, there is no reference to the poverty line – the relevant threshold is $U_h(z_{CE})$ – wherefore VEU does not qualify for identifying the part of the population threatened by poverty.

The last point also holds true for VER which measures whether idiosyncratic and covariate shocks impact on consumption. That is, this concept is not able to identify those threatened by poverty, either. In sharp contrast to every other approach to vulnerability not levels but only changes of consumption matter in the case of VER. When applied econometrically, idiosyncratic and covariate shocks are usually instrumented by the growth rate of average household income ($\Delta\, y_{htv}$) and the growth rate of average village income ($\Delta(\overline{ln\ y_{tv}})$), respectively, of household h in village v at time t as shown in equation 5:

(5) $$\Delta \ln c_{htv} = \alpha + \beta \ln \Delta\, y_{htv} + \gamma \Delta(\overline{ln\ y_{tv}}) + \delta X_{htv} + \Delta\, \varepsilon_{htv}$$

where $\Delta \ln c_{htv}$ denotes the growth rate of consumption per capita between periods t and t-1 and X_{htv} reflects a vector of household characteristics. VER rises with an increasing β. Complete risk sharing is implied by $\beta = 0$. The coefficient γ captures the impact of covariate shocks on consumption.

Although there is a wide range of differing approaches to vulnerability there seem to be at least two characteristics most strands of literature agree upon (cf. Calvo and Dercon, 2005):

1. Vulnerability is a forward-looking concept analyzing something *ex-ante*, and therefore dealing with uncertainties, and not *ex-post* as static poverty measures, which consider actual facts, do.
2. Vulnerability always refers to something negative. That is, vulnerability is concerned with "bad" future outcomes faced by households.

These two similarities are at the root of Calvo and Dercon's (2005) more recent attempt to narrow the multitude of interpretations of vulnerability to a clearly defined and more commonly accepted concept – or, in other words, to end what Hoddinott and Quisumbing (2003) called the "let a hundred flowers bloom" stage of vulnerability research. Within Calvo and Dercon's (2005) vulnerability to poverty framework vulnerability is a probability weighted average of future states of the world-specific indices of deprivation. Their measure does not take into account states of the world above the poverty line. The vulnerability to poverty of household h is calculated as shown in equation 6:

(6) $$Vulnerability\ to\ Poverty_h = 1 - (\sum_{i=1}^{N_h} p_{hi} \times x_{hi}{}^{\alpha}), \quad \text{with}$$

$$0 \leq x_{hi} \leq 1 \quad \text{and} \quad \sum_{i=1}^{N_h} p_{hi} = 1.$$

α ranges between zero and one, p_{hi} denotes the probability of state of the world i to occur and x_{hi} is a state specific degree of deprivation which equals $\frac{\tilde{y}_{hi}}{z}$. $\tilde{y}_{hi}$ is a censored outcome measure. That is, all outcomes where y_{hi} is above the poverty line z are censored at z and consequently do not change the vulnerability measure. There is a total of N_h possible states of the world. The closer (further away) α moves to (from) one the less (more) risk aversion is assumed. By not allowing α to rise beyond one Calvo and Dercon (2005) discard the possibility of risk proclivity.

Among the axioms proposed within the context of vulnerability to poverty the following two stand out and are of relevance for later sections of this paper:[5]

[5] The axioms on which is not elaborated are: (i) axiom of symmetry over states, (ii) axiom of continuity and differentiability, (iii) axiom of scale invariance, (iv) axiom of normalization, (v) axiom of the probability-dependent effect of outcomes, (vi) axiom of probability transfer, and (vii) axiom of constant relative or absolute risk sensitivity. For a in depth discussion of them see Calvo and Dercon (2005).

- The axiom of risk sensitivity implies that while keeping the expected outcome constant an increase in uncertainty faced by a household should be reflected in a higher degree of vulnerability.
- The focus axiom is supposed to ensure that the vulnerability measure is exclusively sensitive to negative future outcomes. Possible positive future outcomes must not be reflected in the measure.[6] In other words, this axiom guarantees that a household is not labeled "non vulnerable" although in a possible future state of the world it faces severe destitution (as it could be, for example, in the case of VEU). Since Calvo and Dercon (2005) are concerned with vulnerability to poverty they interpret the axiom as being adhered to if exclusively outcomes below the poverty line impact on their measure. The concept of vulnerability to poverty shares this characteristic with VEP.

For researchers interested in poverty dynamics the concepts that refer to the poverty line are clearly more relevant than VEU and VER. However, the additional consideration of other indices may enrich any vulnerability assessment substantially. Therefore, in the following section we will present a measure of vulnerability which does not rely on the poverty line as benchmark and adds information to the analysis which is different from the one provided by VEU and VER.

3 Vulnerability to downside risk

We propose a measure of vulnerability to downside risk which chooses a household's current status of wellbeing as reference point to which future consumption changes are compared. The rationale behind this is twofold: *First*, the paternalism inherent in the poverty line is avoided. By using the latter as benchmark people are said to feel deprived as long as they are below it. However, why should these people compare changes in their wellbeing to a threshold they may not even be aware of?[7] *Second*, by determining the poverty line to be the relevant reference point households without a probability of

[6] Calvo and Dercon (2005) offer the following example to illustrate the need for the focus axiom: "…let us imagine that the poor buy each week a state lottery ticket – they spend a very small sum of money, but 'you never know', and there is a 0.001 percent chance of winning to the top prize of $10,000. The following 'policy' measure would make these households less vulnerable [if the focus axiom was not applied] …: increase the top prize to $10 million!"

[7] Arguably there is also a certain degree of paternalism if the current status of wellbeing is chosen as the reference point. For example, if a household is worse off in period t than it was on average during the periods prior to t it may rather compare future consumption changes to its average level of wellbeing in the medium-term. That is, ideally one should use this average as benchmark if information about wellbeing at numerous points in time was available.

falling below it are labeled “non vulnerable” regardless of how much their level of wellbeing may decrease in future. Consequently, the question arises why a household which is likely to fall from high above the poverty line to very close above it should be entirely “non vulnerable” whereas a household which is likely to fall much less, namely from right above the poverty line to right below it, is vulnerable?

Due to the newly chosen reference point the measure of vulnerability to downside risk is based on a re-interpretation of the focus axiom: Now, with this axiom is complied if, and only if, the vulnerability measure in question is exclusively affected by future states of the world in which a household finds itself below its current level of wellbeing.

Certainly, this implies that also outcomes above the poverty line can impact on vulnerability wherefore, in terms of pro-poor policy targeting, such a measure is not useful since the ones threatened by poverty are not identified. But even for poverty reduction the inclusion of households above the poverty line seems reasonable: By concentrating on decreasing degrees of vulnerability in all parts of society (instead of only in potentially poor parts) one allows all households to redirect resources from risk management strategies to growth enhancing activities. It is widely acknowledged that the latter play a crucial role for poverty reduction.

Vulnerability to downside risk is not only different from VEP and vulnerability to poverty but also from VEU and VER: It provides more vulnerability relevant information than VER because it explicitly takes both state specific deprivation *and* probabilities into consideration. By contrast, VER simply analyzes the coefficient of a realized income change and thus disregards the ex-ante probability of this change. Expressed differently, VER rather captures the deprivation than the probability part of vulnerability. With respect to VEU we argue that vulnerability to downside risk provides more vulnerability relevant information since it literally focuses on downside risks for which increases in wellbeing cannot compensate.

The measure of vulnerability to downside risk assigns an index of deprivation x_{hi} – with 0 implying no deprivation (i.e. constant or increased wellbeing) and 1 implying the highest, and only theoretically possible, deprivation (i.e. by 100% decreased wellbeing) – to every state of the world i a household h possibly experiences in the future and weighs it with its probability of occurrence p_{hi}. Thereafter all obtained products are added up. Thus, for N_h possible future states of the world the vulnerability of household h (V_h) is given by equation 7:[8]

(7) $$V_h = \sum_{i=1}^{N_h} (x_{hi}{}^{\alpha} \times p_{hi}) \text{, with}$$

$$0 \leq x_{hi} \leq 1 \quad \text{and} \quad \sum_{i=1}^{N_h} p_{hi} = 1.$$ [9]

α is a parameter measuring risk attitudes. If $\alpha > 1$ risk aversion is assumed and the measure is risk sensitive. Instead, a kind of "risk loving loss aversion" is implied if $0 < \alpha < 1$. In the case of $\alpha = 1$ risk and loss neutrality is assumed. [10] Choosing an appropriate α is not as easy as it might appear at first glance: On the one hand, there is good reason to assume risk aversion as proposed by most studies.[11] On the other hand, in the case of vulnerability to downside risk the degree of deprivation assigned to each relevant state of the world quantifies a loss in welfare – as opposed to a certain level thereof. Taking the literature on risk attitudes into account households might prefer having the choice between a low and a high loss (since their wellbeing rises as the lowest possible loss declines) than having a certain mean loss.[12] In such a case risk proclivity (i.e. $0 < \alpha < 1$) should be assumed since it assigns a higher degree of vulnerability to a certain mean loss and thus implies loss averse households.[13]

In the following section the measure of vulnerability to downside risk will be applied to data from Vietnam. Also, a measure of vulnerability to poverty will be imputed in order to compare the information that both approaches provide with each other. By contrast, we discard the option to estimate a measure of VEP because, as mentioned above, VEP integrates households' risk attitudes only imperfectly.

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[8] Note that this measure belongs to "the class of measures where vulnerability is a probability weighted average of state-specific 'deprivation indices'..." (cf. Calvo and Dercon, 2005). Also note that there is no such thing as an arbitrarily chosen threshold which the measure must surpass in order to assign a household to the group of vulnerable – as there is in the case of VEP. All households facing at least one state of the world in which they are worse off than currently are vulnerable to downside risk. They only differ in their degrees of vulnerability. To determine from which degree of vulnerability onwards a household should be in the focus of policy intervention is not the task of this paper but rather the one of policy makers.

[9] Consequently, the highest degree of vulnerability household h may face equals one, the lowest zero: $V_{h\,max} = 1$ if x_{h1} equals 1 and occurs with certainty, i.e. with a probability p_{h1} of 1; and $V_{h\,min} = 0$ if all x_{hi} equal 0 or every x_{hi} above 0 occurs with a probability p_{hi} of 0. The axiom of "normalization" which Calvo and Dercon (2005) establish "to facilitate interpretation and comparability" is adhered to by these closed boundaries.

[10] Note that $\alpha = 0$ is not advisable since each index of deprivation would equal one in such a case. Consequently, the measure would not adhere to the axiom of probability transfer established by Calvo and Dercon (2005). This axiom requires that the vulnerability measure decreases (increases) if probability from an index of deprivation is transferred to another, lower (higher) index of deprivation.

[11] In fact, the whole concept of VEU as proposed by Ligon and Schechter, 2003) relies on the assumption of risk averse households.

[12] Unfortunately, empirical evidence on loss aversion in developing countries is almost not existent (regarding developed countries see, for instance, Barberis, Huang and Thaler, 2006). However, Dercon (2007) points out that during the 1984-85 famine in Ethiopia pastoralists desperately kept their livestock although selling (or consuming) it would have yielded the certain outcome of mitigating their starvation. A preference towards losing little (by keeping the livestock as long as possible) instead of much might have provoked such a loss adverse behavior.

[13] For a thorough discussion of vulnerability and loss aversion see Günther and Maier (2008).

4 Vulnerability to downside risk and poverty in Vietnam

4.1 Data

The measures of vulnerability to downside risk and vulnerability to poverty are applied to household data from a two wave panel conducted within the context of the research project on "Vulnerability in South-East Asia" in 2007 and 2008. Data was collected from some 2000 households in the three rural Vietnamese provinces Ha Tinh, Thua Thien-Hue and Dak Lak. The sample of households was selected via a three-stage cluster-sampling procedure. The three provinces served as strata. From them sub-districts were selected with a probability proportional to the number of households they host. Special attention was paid to population density in order to ensure that densely, as well as less densely populated sub-districts were covered adequately. Within each sub-district two villages were chosen again with a probability proportional to size. In a last step ten households from each village were randomly incorporated into the sample.

The questionnaire used for the survey covered information about household member characteristics such as demographics, education and health; agriculture; off-farm and self-employment; borrowing, lending, public transfers and insurance; expenditures; assets; and housing conditions. Also, households were asked which negative shocks they experienced between both waves (henceforth referred to as the reference period). This rich data set allows us to (i) predict the probability of shocks during the reference period with variables from the beginning of the reference period, (ii) estimate the impact of shocks during the reference period on consumption during the reference period (our chosen dimension of wellbeing), and consequently (iii) quantify households' vulnerability at the beginning of the reference period.

Given that we only dispose of information regarding negative shocks we have to disregard any positive event that may occur during the reference period. This data limitation may lead to an overestimation of vulnerability to downside risk and poverty. For example, if in state of the world i household h is said to be below the poverty line because it suffers from a flood a deprivation index smaller than one is assigned to this state (recall that a deprivation index equal to one represents no deprivation). We can capture this with our data. If, however, household h is not only expected to experience a flood in state of the world i but also to win the lottery an at least greater (if not equal to one) deprivation index should be assigned. This we cannot capture with our data. The results presented below should be interpreted with this data driven drawback in mind.

4.2 Methodology

We define relevant future states of the world faced by household h (N_h), i.e. states of the world where households are below their current level of wellbeing and below the poverty line, respectively, and estimate their probabilities (p_{hi}), as well as their deprivation indices (x_{hi}). The method we apply to quantify state of the world specific consumption shortfalls and probabilities is similar to the one from Calvo and Dercon (2007). It is the same for vulnerability to downside risk and vulnerability to poverty because within the framework of both concepts "vulnerability is a probability weighted average of state-specific 'deprivation indices'" (Calvo and Dercon, 2005). However, the way in which consumption shortfalls are transformed into deprivation indices differs between both measures due to their unlike benchmarks.

The number of possible future scenarios for household h (N_h) depends on the number of risks this household is exposed to. Assume that household h faces J_h downside risks with a certain probability. With the help of J_h the number of possible future states of the world faced by household h (N_h) can then be derived via equation 8:

$$N_h = \sum_{j=0}^{J_h} \frac{J_h!}{(J_h - j)!\,j!} \qquad (8)$$

To exemplify equation 8, imagine a household h that faces and 3 downside risks a, b, and c (i.e. $J_h = 3$). This household faces the following $\sum_{j=0}^{3} \frac{3!}{(3-j)!\,j!} = 8$ relevant future states of the world:

- $\frac{3!}{(3-0)!0!} = 1$ state of the world in which no risk occurs;
- $\frac{3!}{(3-1)!1!} = 3$ states of the world in which one risk occurs (i.e. a, b, or c);
- $\frac{3!}{(3-2)!2!} = 3$ states of the world in which two risks occur (i.e. a and b, a and c, or b and c;); and
- $\frac{3!}{(3-3)!3!} = 1$ state of the world in which all risks occur (i.e. a, b, and c).

From all the adverse events covered by the questionnaire the five most common shocks, namely flooding (experienced by 21.5% of households), bad weather (including storm, heavy rainfall, snow, ice rain; 18.8%), health shock (including illness, accident, death; 10.1%), livestock disease (7.1%), and crop pest (5.7%), were selected for the computation of households' vulnerability.[14] To address at least partly the problem of heterogeneous income streams at risk and the following incomparability of households we limit our sample to households that produce crops (due to crop pest) and hold livestock (due to livestock disease) during the reference period. Thus, our sample size decreases from 2,148 to 1,749 households, i.e. to 81.4% of the original size. According to equation 8 the consideration of five possible events theoretically leads to $\sum_{j=0}^{5} \frac{5!}{(5-j)!j!} = 32$ possible states of the world the households face. Whether these states impact on measures of vulnerability depends on their probability and severity.

With regard to the probability of a future state of the world i (p_{hi}) one has to acknowledge that risk-specific probabilities are not likely to be independent from each other. For example, a flood might increase the risk of an illness. Also, the risk of death and other individual-related risks are mutually exclusive. That is, in the case of a state of the world, in which, for instance, two risks a and b take place and one other c does not, the correct way to define its probability would be

(9) $$p_{hi} = P(\gamma|\delta)$$

with $\gamma \cong P(risk_a \cap risk_b) = P(risk_a) \times P(risk_b|risk_a)$ and $\delta \cong P(1 - risk_c)$. To obtain this probability is a very complex task since one has to estimate the covariance of risk probabilities, as well as to identify the causalities running between the risks in question. Because such an endeavor would go far beyond the scope of this paper independent risk-specific probabilities will be assumed in its remainder.[15] Therefore, the probability that household h experiences state of the world i is given by equation 10.

(10) $$p_{hi} = \prod_{j=1}^{q_{hi}} p_{hij} \times \prod_{l=1}^{J_h, l \neq j} (1\text{-}\, p_{hil})$$

[14] Summary statistics for all variables and subsample are provided in the appendix. Note that another frequent shock was drought. However, the occurrence of a drought did not significantly impact on consumption. Also, drought and flood might be mutually exclusive why the former was discarded from the analysis

[15] Note that independent risk-specific probabilities are also assumed in Calvo and Dercon (2007), as well as in other vulnerability related articles. Also note that none of the sampled households used for the empirical part of this study experienced more than one shock during the reference period. That is, when predicting shock probabilities it is impossible to construct a dependent variable that takes the value one if a household experienced two shocks and zero if it experienced zero or one shock.

where $\prod_{j=1}^{q_{hi}} p_{hij}$ yields the probability that q risks will occur in state of the world i; and $\prod_{l=1}^{J_h, l \neq j}$ (1- p_{hil}) represents the probability that all other risks do not take place in state of the world i.[16]

While the computation of N_h and p_{hi} does not differ between the measures of vulnerability to downside risk and vulnerability to poverty, the one of state specific deprivation indices does: In the case of vulnerability to downside risk the index of deprivation assigned to household h in state of the world i (x_{hi}) in which q downside risks take place is given by equation 11:

$$x_{hi} = \frac{\sum_{j=1}^{q_{hi}} s_{hij}}{y_h} \qquad (11)$$

where $\sum_{j=1}^{q_{hi}} s_{hij}$ is household's h total consumption shortfall caused by q risks that occur in state of the world i and y_h denotes household's h current consumption (or any other dimension of wellbeing).[17]

With respect to vulnerability to poverty, however, the respective index of deprivation equals:

$$x_{hi} = \frac{\tilde{y}_{hi}}{z} \qquad (12)$$

where $\tilde{y}_{hi} = y_h - \sum_{j=1}^{q_{hi}} s_{hij}$, i.e. household's h current consumption minus its total consumption shortfall caused by q risks that occur in state of the world i. $\tilde{y}_{hi}$ is censored at the poverty line z. In other words, for all states of the world where $y_h - \sum_{j=1}^{q_{hi}} s_{hij} > z$ the index of deprivation x_{hi} equals 1. Note that in the case of both vulnerability measures x_{hi} ranges between zero and one.

4.3 State of the world specific deprivation indices

The first component needed for the computation of vulnerability are state of the world specific deprivation indices. More precisely, expected consumption shortfalls for every state of the world have to be quantified and transformed via the aforementioned equations 11 and 12. We estimate expected consumption shortfalls by regressing the log of per capita consumption of household i during the

[16] Note that for the state of the world in which $x_{hi} = 0$, i.e. in which nothing happens, the first part of the right hand side of equation 10 is equal to $\prod_{j=1}^{0} p_{hij}$ = 1 since the neutral element of a product is 1. Likewise, for the state of the world in which $x_{hi} = X_h$, i.e. in which all possible risks occur, the second part of the right hand side of equation 10 is equal to $\prod_{j=1}^{0} p_{hij}$ = 1

[17] Equation 11 implicitly assumes that consumption shortfalls due to different events add up linearly. This rather unlikely assumption is necessary because none of the sampled households used for the empirical part of this study experienced more than one shock during the reference period. That is, it is impossible to add an explanatory variable to the consumption regression that takes the value one if a household experienced two shocks and zero if it experienced zero or one shock.

reference period ($\ln{(cons)_{i0}}$) on a set of five dummies which represent the most frequent shocks j (D_{ji0}) mentioned above, as well as on a bunch of household and household head characteristics from the time prior to the reference period (X'_{i-1}):

$$\ln{(cons)_{i0}} = \alpha + \sum_{j=1}^{5} \beta_j * D_{ji0} + \gamma * X'_{i-1} + \varepsilon_{i0} \quad (13)$$

β_j is our coefficient of interest because it indicates whether shock j reduces consumption significantly why it can be used to calculate the *average expected* consumption shortfall due to the respective event. The vector X'_{i-1} includes lagged household wealth (as a vector of consumption quintile dummies[18]), demographic characteristics of the household (size, number of children younger than 16, number of elderly older than 64), education (as a vector of dummies indicating the highest educational attainment within the household), and household head characteristics (as a vector of age dummies, ethnicity dummy, female dummy). No location dummies are included because they could possibly soak up a significant impact of the dummies which represent covariate shocks. Also, other potential predictors of consumption, such as occupation, as well as access to insurance and credit, are excluded since they proxy risk management capacities. However, we want β_j to capture the impact of shocks after all consumption smoothing strategies have been implemented which would not be the case if an additional covariate soaked up the effect of such a strategy. Similarly, we do not include income change during the reference period as a covariate because it would capture the income loss caused by shocks.

The first three columns of table 1 show the results of our benchmark regression with different ways of clustering standard errors. In the first column robust standard errors are used whereas in the second and third column standard errors are clustered at the village (218 clusters) and sub-district (110 clusters) level, respectively. There is no sign of a great deal of autocorrelation within villages or sub-districts since the significance of coefficients basically does not change. Three shock dummies reduce consumption significantly (at the 1% level). Of these livestock disease has the lowest point estimate (-.159), followed by bad weather (-.141) and flood (-.120) which is somewhat surprising since the latter two ought to be of more covariate nature than the former. Health shocks and crop pests are no significant predictors of consumption.

The other covariates exhibit plausible correlations: Lagged wealth measured by consumption quintile dummies is a strong predictor of current consumption. Household size and number of children are

[18] Instead of consumption quintile dummies also the log of lagged per capita consumption was tried as a covariate. However, the coefficient of this variable was not significantly different from zero possibly indicating substantial attenuation bias.

associated with lower, education with higher consumption. Female headed households, as well as households with a head from an ethnic minority consumed significantly less during the reference period. Perhaps a bit surprisingly, the age of household heads only impacts significantly negatively on consumption if the head is older than seventy. The benchmark specification is able to explain 44.6% of the variation in the dependent variable

It is unlikely that shocks impact homogeneously on consumption. For example, relatively poor and risk averse households may be more willing to insure consumption than relatively rich households by means of costly smoothing strategies such as taking children out of school (cf. Chetty and Looney, 2006). On the other hand, relatively rich households may be more able to insure consumption than relatively poor households by relying on credit and insurance markets. Therefore, we estimate equation 13 for four mutually exclusive subsamples, namely for (i) households that are extremely poor in wave one (i.e. consume less than USD PPP 1.25 per capita and day), for (ii) households that are moderately but not extremely poor (i.e. consume between USD PPP 1.25 and 2 per capita and day), for (iii) a group of households that we label non-poor, non-rich households (which consume between USD PPP 2 and 3 per capita and day), and for (iv) rich households (which consume USD PPP 3 and more per capita and day).

As can be deduced from table 2 there are enough shocks in every subsample to obtain meaningful β_j. Floods and bad weather shocks are most common in all groups, followed by health shocks, livestock diseases and crop pests. Crop pests occur only to 2.4% of the extremely poor households wherefore the respective coefficient might be statistically underpowered. However, even in the benchmark regression where 5.7% of the observations are affected by crop pests this event is no significant predictor of consumption.

The four right columns of table 1 show results of the subsample regressions. For obvious reasons consumption quintile dummies are excluded from the subsample regressions. The impact of shocks on consumption is fairly heterogeneous between the different specifications: While the impact of health shocks and crop pests is statistically indistinguishable from zero in all subsamples, the rich suffer significantly from floods, livestock diseases and bad weather, the non-poor non-rich from floods and bad weather, the moderately but not extremely poor from bad weather and the extremely poor from livestock diseases and bad weather.

We use β_j of every significant shock to quantify sub-sample specific average consumption shortfalls caused by these events during reference period. According to Halvorsen and Palmquist (1980) the coefficient of a dummy variable that explains a logged outcome variable has to be transformed via $\left(\exp(\beta_j) - 1\right) * 100$ in order to represent the difference in percent between households for which the dummy equals one and households for which it equals zero. Table 3 shows results of the different steps included in this quantification: The top contains the relevant, i.e. significant, point estimates. Below they are transformed into consumption changes in percent from the total per capita consumption during the reference period before further below the associated mean consumption shortfall is presented in monetary terms. At the bottom the consumption shortfall is deflated to monetary values from wave one.

As mentioned above, the rich suffer significantly from all three shocks in question. Their lowest event specific mean shortfall (USD PPP 198.57 in case of livestock disease) is higher than shortfall in the other subsamples. This lack of consumption smoothing may be due to several factors such as a small degree of risk aversion, a relatively large income stream at risk and more consumption that can painlessly be cut. The result is in line with a study from Wagstaff and Lindelow (2010) who find that in neighboring Laos costs of shocks are mostly higher for the better off. The non-poor households cannot smooth their consumption against floods and bad weather, the extremely poor not against livestock diseases and bad weather. In the case of the extremely poor the mean consumption shortfall due to a livestock disease is with UDS PPP 191.58 very large suggesting that they have very limited capacities to cope with such an event. Finally, the moderately but not extremely poor seem to perform best in insuring consumption against shocks. Only bad weather leads to a significant but relatively small consumption shortfall of USD PPP 90.52. However, this finding does not necessarily imply that the moderately do not suffer a great deal once they are hit by a shock. As Chetty and Looney (2006) point out, poor households may be very reluctant to reduce consumption further. Instead, they may apply costly coping strategies which could negatively affect other dimensions of wellbeing.

Table 4 shows summary statistics of expected consumption shortfalls in every relevant state of the world for the whole sample. Recall that although only 8 states are presented *de facto* we control for 32 states. However, since health shocks and crop pests which would account for this higher number are not significant we disregard them when constructing the final vulnerability measures. Floods and bad weather hit households on average much worse than livestock diseases. This result refutes the implausible finding from the benchmark regression for the entire sample where the point estimate for livestock diseases was higher than for the other two events.

Using equations 11 (for vulnerability to downside risk) and 12 (for vulnerability to poverty) the computed consumption shortfalls are transformed into state of the world-specific deprivation indices. We assume risk averse households and set alpha in the case of vulnerability to downside risk equal to two and in the case of vulnerability to poverty equal to one third. For the calculation of the latter vulnerability measure the USD PPP 1.25 per capita and day poverty line is used.

4.4 State of the world specific probabilities

Vulnerability measures that are a probability weighted average of state-specific deprivation indices require information about state of the world specific probabilities. We predict household specific probabilities of the three events that significantly lower consumption if they take place. We start with regressing the shock dummies on sub-district dummies (results not reported). The respective adjusted R squared is a measure of the covariance of shocks with a flood being the most covariate (0.298), followed by bad weather (0.182), and livestock diseases (0.072). Our aim is to predict shock occurrence as precisely as possible and the location of a household matters a lot in explaining its susceptibility to (covariate) shocks. Therefore, we estimate linear probabilities separately for the occurrence of a flood, a livestock disease and bad weather via equation 14

$$shock_{i0} = \alpha + \beta_{sd} * D_i' + \gamma * X_{i-1}' + \varepsilon_{i0} \tag{14}$$

where $\mathrm{X}_{\mathrm{i}-1}'$ contains the same covariates as in equation 13. D_{i}' is a vector that contains 110 sub-district dummies.

Table 5 presents the results from equation 14. For reasons of comparison for each shock equation 14 was also calculated without sub-district dummies. The specifications with sub-district dummies explain 30.4% of the variation in flood occurrence, 18.1% in the one of bad weather, and 7.7% in the one of livestock diseases. Sub-district dummies substantially soak up the effects some covariates have in the specification without location variables. Thus, the less wealthy you are the more likely you are hit by a flood or bad weather. However, within sub-districts this correlation is not significantly different from zero – with the exception of two wealth dummies in the case of bad weather that are slightly significant

– suggesting that poorer sub-districts are located in areas that are prone to floods and adverse weather shocks.

The coefficients of the other covariates strengthen the view that shock probabilities are mainly a matter of location: Household demography and household head's age generally matter little. Education is significantly and non-linearly correlated with the occurrence of livestock diseases but this association dissolves almost entirely as soon as location dummies are included. Surprisingly, households headed by a female (member of an ethnic minority) are less susceptible to a livestock disease (bad weather shock) even within sub-districts.

Since linear regressions are used to predict probabilities the latter may exceed 100% or fall below 0%. In respective cases probabilities are bounded at zero and one for the subsequent analysis. Instead, probabilities for all 8 states of the world were calculated according to equation 10. Their summary statistics are provided in table 6. The median household has almost a fifty-fifty chance that a bad state of the world happens or not. The probability that the household will not experience any adverse event is 54.4%. Also, the median household is most likely affected by bad weather (10.2%), and a flood (8.2%). By contrast, a livestock disease is with a probability of 2.8% fairly unlikely. Mean probabilities are in general above median probabilities. On average a flood (17.2%) is more likely than bad weather (16.2%) which in turn is more likely than a livestock disease (5.5%). Since independent probabilities are assumed probabilities of states of the world with more than one adverse event are by construction far below probabilities of states with only one shock.

Examining the probabilities of different states of the world a little further we analyze them by the four sub-samples we used to estimate the impact of shocks on consumption. Table 7 shows the sum of probabilities of the 7 states of the world in which at least one adverse event takes place by sub-sample. Generally, in terms of median and mean probabilities there is a clear trend towards lower probabilities in less poor subsamples suggesting better risk prevention capacities of consumption richer households. The probabilities of the rich subsample are significantly lower than the ones of the non-poor, non-rich subsample which in turn are significantly below the probabilities of the moderately but not extremely poor.

4.5 Vulnerability to downside risk and poverty

Summary statistics of vulnerability to downside risk and vulnerability to poverty in Vietnam are shown in table 8. Of 1741 households for which vulnerabilities could be computed 75 are not vulnerable to downside risk. That is, they experience the state of the world in which nothing happens with a probability of one and/or the deprivation indices in states of the world with a probability above 0% are equal to zero. By contrast, 1257 out of 1741 (72.2%) households are not vulnerable to extreme poverty. This discrepancy between both vulnerability measures indicates that the information they provide is highly complementary as opposed to supplementary. Median and mean values of the whole sample cannot really be interpreted. It is merely possible to compare the vulnerability to poverty of rural Vietnamese households in 2007 to the one of rural Ethiopian households in 1994, 1999, and 2004. Mean vulnerability to poverty ranges between .039 (in 1994 and 2004) and .049 (in 1999), i.e. far above the .0172 estimated for Vietnam. However, it should be noted that the results are not really comparable since they were recorded in different countries, at different points in time and with different variables underling the quantification of state of the world specific severities and probabilities.

Table 9 shows summary statistics for both vulnerability measures by the subsamples used throughout this study. By construction the extremely poor are most vulnerable to extreme poverty. The difference between this sub-sample and the others is very pronounced, its mean vulnerability is more than 50 times higher than the one of the moderately but not extremely poor households. This result is driven by the data limitation mentioned above: Extremely poor households will be said to stay extremely poor and become even poorer if only negative events are considered for the quantification of state specific deprivation indices. Recall that the moderately but not extremely poor households perform very well in risk coping (only bad weather shocks impact significantly on consumption) why the 95% confidence interval of their vulnerability to poverty overlaps with the interval of the vulnerability of non-poor, non-rich households. Even among rich sub-sample at least a few households are vulnerable to poverty as is indicated by a mean vulnerability of above zero.

The extremely poor are not just most vulnerable to poverty but also to downside risk. Their respective 95% confidence interval does not overlap with the one of any other group. Rich households constitute the second most vulnerable sub-sample followed closely by the group of the non-poor, non-rich households. The by far least vulnerable group are the moderately but not extremely poor households whose confidence interval's upper bound is clearly below the lower bound of the other sub-samples.

That is, moderately but not extremely poor households seem to be able to manage risk best – at least in terms of consumption. They seem to do so not by better preventing risks from happening (their probabilities of bad states of the world are the second highest) but by better coping with and mitigating the impact of realized adverse events. By which means these households manage their risk that efficiently is not addressed in this paper but an interesting question for future research. Again it becomes obvious that the measure of vulnerability to downside risk sheds additional light on the vulnerability of rural households in Vietnam: Certainly, the group of the moderately but not extremely poor households is on average more vulnerable to poverty than the richer subsamples. But they are at the same time less vulnerable to downside risk.

Figure 1 confirms these insights: The local linear regressions of vulnerability to downside risk on the log of per capita consumption from wave one shows the lowest level of vulnerability at a log consumption value of around 6.4, i.e. around USD PPP 1.64 per capita and day. To the left of this point vulnerability increases strongly, to its right slightly. Vulnerability among less poor households peaks at a log consumption of around 7.1, i.e. around USD PPP 3.3 per capita and day which is twice as much as the consumption of the least vulnerable.

Both vulnerability measures are positively correlated with each other. This correlation is statistically significant at the 1%-level, the respective coefficient equals 0.5. Figure 2 depicts an even stronger association for the subsample of households that have a vulnerability to poverty greater than zero: On average households with a vulnerability to poverty of .1 have a vulnerability to downside risk which is slightly below .1.

We finally turn to the prediction of consumption and poverty dynamics. The prediction quality of both vulnerability measures is likely to suffer substantially from the fact that no positive events have been considered for their calculation. The fact that average per capita consumption increased by USD PPP 1.02 shows that such events must have played a crucial role during the reference period. Out of 247 extremely poor households 87 stayed extremely poor, whereas 160 managed to move out of poverty. The latter outweigh by far the 62 households that fell into poverty during the reference period. That is, also among the poor windfalls profits were substantial. Figures 3 and 4 contain local linear regressions of both vulnerability measures on consumption change during the reference period. The figures seem to reflect the drawback of the data underlying the vulnerability measures: Both vulnerability to downside risk (figure 3) and to poverty (figure 4) increase with a more positive consumption change. However, what at first sight could be labeled bad prediction quality might rather be proof that households with greater exposure to positive “risks” are at the same time more prone to downside risk.

5 Conclusion

With this paper we aim to contribute to the concept and measurement of vulnerability. After having discussed common concepts of vulnerability we propose a measure of vulnerability to downside risk which belongs to “the class of measures where vulnerability is a probability weighted average of state-specific ‘deprivation indices’...” (cf. Calvo and Dercon, 2005). However, it differs from other approaches to vulnerability in its choice of the relevant benchmark. Instead of relying on a pre-determined threshold such as the poverty line it takes a household’s current status of wellbeing as reference point. Due to the newly chosen reference point the proposed measure of vulnerability interprets the focus axiom differently as has been done so far: Only possible future states of the world which imply a lower level of wellbeing than the current one affect the vulnerability of a household.

We opt for this benchmark since it offers additional insights into the vulnerability of households: Our measure captures consumption shortfalls above the poverty line (as opposed to VEP and vulnerability to poverty), is not affected by positive changes in wellbeing (as is VEU) and considers both the deprivation and probability of different states of the world (as opposed to VER).

We apply the measure of vulnerability to downside risk and poverty to a two wave household panel from rural Vietnam. Following the empirical approach from Calvo and Dercon (2007) we identify relevant states of the world to which we assign probabilities and deprivation indices. Unfortunately, our empirical application suffers from the unavailability of information about unexpected positive events wherefore only negative shocks are considered. The impact of shocks on consumption is heterogeneous across different groups. Households consuming more than USD PPP 3 per capita and day are most affected whereas moderately but not extremely poor households are least affected. In terms of probabilities, the poorer households are the more likely they experience a bad state of the world in future.

Although both vulnerability measures are significantly positively correlated they provide complementary information. While moderately but not extremely poor households are on average more vulnerable to poverty than richer households the measure of vulnerability to downside risk reveals that they manage downside risk better than any other group of households. We therefore recommend the complementary use of a measure of vulnerability to downside risk in any holistic vulnerability assessment.

Table 1: Determinants of consumption							
Dependent variable: log of per capita consumption - wave 2							
	All (robust std error)	All (std error clustered at village level)	All (std err clustered at sub district level)	Below $1.25 per capita and day	Between $1.25 and $2 per capita and day	Between $2 and $3 per capita and day	Above $3 per capita and day
Flood	-0.120***	-0.120***	-0.120***	-0.0745	-0.0270	-0.174***	-0.241***
	(0.0278)	(0.0281)	(0.0305)	(0.0857)	(0.0537)	(0.0564)	(0.0591)
cr_pest	-0.0513	-0.0513	-0.0513	0.0525	0.00276	-0.0913	-0.0642
	(0.0429)	(0.0465)	(0.0511)	(0.174)	(0.0894)	(0.0699)	(0.113)
lst_disease	-0.159***	-0.159***	-0.159***	-0.407***	-0.119	-0.0998	-0.138**
	(0.0394)	(0.0411)	(0.0409)	(0.134)	(0.0817)	(0.0651)	(0.0612)
bad_weather	-0.141***	-0.141***	-0.141***	-0.179*	-0.124**	-0.122**	-0.188***
	(0.0290)	(0.0307)	(0.0299)	(0.0962)	(0.0571)	(0.0557)	(0.0488)
Health	-0.0457	-0.0457	-0.0457	-0.0286	-0.0281	-0.0645	-0.0674
	(0.0378)	(0.0392)	(0.0410)	(0.0908)	(0.0580)	(0.0938)	(0.0704)
pccons_qnt1_w1	-0.729***	-0.729***	-0.729***				
	(0.0410)	(0.0420)	(0.0432)				
pccons_qnt2_w1	-0.519***	-0.519***	-0.519***				
	(0.0354)	(0.0364)	(0.0357)				
pccons_qnt3_w1	-0.346***	-0.346***	-0.346***				
	(0.0348)	(0.0362)	(0.0361)				
pccons_qnt4_w1	-0.225***	-0.225***	-0.225***				
	(0.0341)	(0.0355)	(0.0347)				
w1_hhsize	-0.0230**	-0.0230**	-0.0230**	-0.0206	0.00163	-0.0222	-0.0604***
	(0.0104)	(0.0110)	(0.0101)	(0.0211)	(0.0195)	(0.0223)	(0.0227)
Children	-0.0768***	-0.0768***	-0.0768***	-0.0887***	-0.0691***	-0.0962***	-0.0612**
	(0.0136)	(0.0140)	(0.0139)	(0.0327)	(0.0194)	(0.0297)	(0.0288)
Elderly	-0.0368	-0.0368	-0.0368	-0.0105	-0.0267	-0.104**	-0.00940
	(0.0247)	(0.0259)	(0.0284)	(0.0552)	(0.0553)	(0.0472)	(0.0520)
hi_some_pr	-0.0854**	-0.0854*	-0.0854*	-0.0915	0.0152	-0.125	-0.201*
	(0.0419)	(0.0452)	(0.0459)	(0.105)	(0.0753)	(0.0857)	(0.106)
hi_pr	-0.00518	-0.00518	-0.00518	0.0520	-0.0938	0.0158	0.0590
	(0.0485)	(0.0456)	(0.0444)	(0.110)	(0.0782)	(0.0780)	(0.145)
hi_some_lsc	-0.0192	-0.0192	-0.0192	-0.0269	-0.00199	-0.0198	-0.0682
	(0.0301)	(0.0313)	(0.0317)	(0.0727)	(0.0512)	(0.0549)	(0.0735)
hi_some_usc	0.127***	0.127***	0.127***	0.347*	0.112*	0.156**	0.113
	(0.0432)	(0.0445)	(0.0466)	(0.189)	(0.0617)	(0.0730)	(0.0798)
hi_usc	0.0546	0.0546*	0.0546*	0.00757	0.0812	0.0413	0.0800
	(0.0334)	(0.0329)	(0.0327)	(0.112)	(0.0614)	(0.0559)	(0.0610)
hi_above_sc	0.131***	0.131***	0.131***	0.108	0.199**	0.142*	0.138**
	(0.0369)	(0.0399)	(0.0391)	(0.112)	(0.0875)	(0.0760)	(0.0628)
hd_age030	-0.0650	-0.0650	-0.0650	0.0973	0.0492	-0.133*	-0.184*
	(0.0449)	(0.0488)	(0.0532)	(0.113)	(0.0841)	(0.0688)	(0.111)
hd_age3140	-0.00935	-0.00935	-0.00935	0.158**	-0.0181	-0.0342	-0.0403
	(0.0288)	(0.0303)	(0.0292)	(0.0739)	(0.0494)	(0.0495)	(0.0775)
hd_age5160	-0.0254	-0.0254	-0.0254	0.286***	-0.0298	-0.115*	-0.0104
	(0.0323)	(0.0333)	(0.0333)	(0.0989)	(0.0536)	(0.0675)	(0.0628)
hd_age6170	-0.0586	-0.0586	-0.0586	0.0112	-0.108	-0.0442	-0.0367
	(0.0441)	(0.0453)	(0.0445)	(0.123)	(0.104)	(0.0799)	(0.0879)
hd_age71	-0.148**	-0.148**	-0.148**	-0.0461	-0.181*	-0.0784	-0.263*
	(0.0592)	(0.0620)	(0.0650)	(0.122)	(0.101)	(0.108)	(0.136)
Minor	-0.202***	-0.202***	-0.202***	-0.261***	-0.263***	-0.186***	-0.0562
	(0.0315)	(0.0407)	(0.0434)	(0.0797)	(0.0667)	(0.0665)	(0.0931)
Continued on next page							

Table 1: continued							
Female	-0.0700**	-0.0700**	-0.0700**	-0.252**	-0.0448	-0.0484	-0.0245
	(0.0316)	(0.0302)	(0.0317)	(0.0978)	(0.0542)	(0.0688)	(0.0577)
Constant	7.600***	7.600***	7.600***	6.773***	6.883***	7.366***	7.686***
	(0.0523)	(0.0572)	(0.0572)	(0.120)	(0.0962)	(0.0929)	(0.119)
Observations	1741	1741	1741	247	488	510	496
Adjusted R-squared	0.446	0.446	0.446	0.210	0.092	0.127	0.131

Notes: OLS regressions; standard errors in parentheses; * denotes significance at 10%-level, ** at 5%-level, *** at 1%-level; 218 village clusters; 110 sub-district clusters; three left columns include all households; four right columns include households of respective subsamples; standard errors of subsample regressions are robust; left out categories: see summary statistics in appendix

Table 2: Shock frequency by wealth group		Households consuming … per capita and day			
		<1.25	>=1.25&<2	>=2&<3	>=3
share of households experiencing … shock	N	248	488	511	502
	flood	0.339	0.254	0.188	0.143
	crop pest	0.024	0.049	0.065	0.074
	livestock disease	0.060	0.076	0.074	0.070
	bad weather	0.198	0.211	0.202	0.145
	health	0.077	0.109	0.096	0.110

Table 3: Consumption shortfall due to shocks				
Sub-sample:	<1.25	>=1.25&<2	>=2&<3	>=3
coefficients of interest:				
Flood	.	.	-0.174	-0.241
lst_disease	-0.407	.	.	-0.138
bad_weather	-0.179	-0.124	-0.122	-0.188
as % of consumption in wave 2				
Flood	0	0	15.97	21.42
lst_disease	33.44	0	0	12.89
bad_weather	16.39	11.66	11.49	17.14
as mean consumption shortfall in wave 2 (PPP USD 2005)				
Flood	0	0	187.75	359.78
lst_disease	208.88	0	0	216.50
bad_weather	102.38	98.70	135.08	287.89
as mean consumption shortfall in wave 1 (PPP USD 2005)				
Flood	0	0	172.20	329.98
lst_disease	191.58	0	0	198.57
bad_weather	93.90	90.52	123.89	264.04

Table 4: Consumption shortfalls by states of the world				
states of the world	shocks occurring	median	mean	std dev
1	flood	118.02	145.02	184.71
2	livestock disease	0	84.16	123.95
3	bad weather	112.13	150.56	125.97
4	flood and livestock disease	155.72	229.18	276.48
5	flood and bad weather	209.24	295.58	304.23
6	livestock disease and bad weather	145.92	234.72	232.05
7	flood, livestock disease and bad weather	259.48	379.74	396.86
8	none	0		

Table 5: Determinants of shock occurrence						
Dependent variable: dummy indicating occurrence of						
	Flood	flood	livestock disease	livestock disease	bad weather	bad weather
pccons_qnt1_w1	0.197***	0.0528	-0.0115	-0.0155	0.128***	0.0403
	(0.0341)	(0.0348)	(0.0220)	(0.0264)	(0.0322)	(0.0356)
pccons_qnt2_w1	0.120***	0.0190	0.0124	0.00579	0.118***	0.0571*
	(0.0308)	(0.0284)	(0.0220)	(0.0245)	(0.0302)	(0.0305)
pccons_qnt3_w1	0.0781***	0.00189	0.00831	0.00196	0.0959***	0.0493
	(0.0294)	(0.0277)	(0.0214)	(0.0227)	(0.0294)	(0.0300)
pccons_qnt4_w1	0.0481*	0.0104	-0.0210	-0.00813	0.0735***	0.0513*
	(0.0278)	(0.0258)	(0.0194)	(0.0207)	(0.0283)	(0.0278)
w1_hhsize	0.000642	0.00316	-0.00224	0.00135	-0.0149*	-0.00859
	(0.00891)	(0.00800)	(0.00635)	(0.00649)	(0.00851)	(0.00827)
children	-0.00699	0.00321	-0.000805	-0.00284	0.00570	0.00941
	(0.0126)	(0.0112)	(0.00860)	(0.00880)	(0.0121)	(0.0113)
elderly	-0.00352	-0.0326*	-0.0150	-0.0168	0.0145	0.00303
	(0.0217)	(0.0195)	(0.0124)	(0.0132)	(0.0223)	(0.0224)
hi_some_pr	-0.0207	-0.0556	-0.0455*	-0.0191	0.0613	0.0589
	(0.0400)	(0.0356)	(0.0253)	(0.0259)	(0.0407)	(0.0385)
hi_pr	0.0435	0.0426	-0.0440	-0.0313	0.0234	0.00724
	(0.0462)	(0.0405)	(0.0270)	(0.0272)	(0.0405)	(0.0411)
hi_some_lsc	-0.00546	-0.00239	-0.0533***	-0.0308*	0.0247	0.0273
	(0.0287)	(0.0248)	(0.0185)	(0.0179)	(0.0272)	(0.0255)
hi_some_usc	0.0227	0.0354	-0.0568**	-0.0288	-0.0239	-0.0115
	(0.0414)	(0.0366)	(0.0248)	(0.0243)	(0.0342)	(0.0318)
hi_usc	0.000192	0.0167	-0.0161	-0.00915	0.0284	0.0224
	(0.0316)	(0.0269)	(0.0229)	(0.0226)	(0.0304)	(0.0283)
hi_above_sc	-0.0242	-0.0276	-0.0450**	-0.0349	0.0304	0.0207
	(0.0337)	(0.0326)	(0.0226)	(0.0219)	(0.0334)	(0.0322)
hd_age030	0.0763	0.0542	0.0325	0.0338	-0.0399	-0.0585
	(0.0485)	(0.0424)	(0.0345)	(0.0332)	(0.0375)	(0.0371)
hd_age3140	0.0365	0.0304	-0.0347*	-0.0214	-0.00786	-0.0169
	(0.0284)	(0.0248)	(0.0182)	(0.0184)	(0.0260)	(0.0240)
hd_age5160	-0.00718	-0.0158	0.0110	0.0119	0.0435	0.0342
	(0.0289)	(0.0263)	(0.0208)	(0.0199)	(0.0288)	(0.0274)
hd_age6170	-0.0319	-0.0164	-0.0249	-0.0337	0.0449	0.0208
	(0.0385)	(0.0352)	(0.0230)	(0.0241)	(0.0395)	(0.0384)
hd_age71	-0.0591	-0.0109	-0.0265	-0.0200	-0.0226	-0.0516
	(0.0500)	(0.0455)	(0.0276)	(0.0301)	(0.0521)	(0.0513)
minor	-0.0272	-0.00119	0.0105	0.0439*	-0.101***	-0.0451*
	(0.0279)	(0.0311)	(0.0183)	(0.0254)	(0.0235)	(0.0267)
female	0.00105	-0.00582	-0.0423***	-0.0373**	-0.0165	-0.000102
	(0.0285)	(0.0255)	(0.0150)	(0.0163)	(0.0274)	(0.0263)
Constant	0.136***	0.0961	0.135***	0.101	0.155***	0.265**
	(0.0420)	(0.0851)	(0.0317)	(0.0646)	(0.0383)	(0.120)
Sub-district dummies	No	yes	no	yes	no	yes
Observations	1741	1741	1741	247	488	510
Adjusted R-squared	0.446	0.446	0.446	0.210	0.092	0.127

Notes: OLS regressions; robust standard errors in parentheses; * denotes significance at 10%-level, ** at 5%-level, *** at 1%-level; left out categories: see summary statistics in appendix

Table 6: Probabilities of states of the world					
states of the world	shocks occurring	# of households with prob.=0	median	mean	std dev
1	flood	241	0.088	0.172	0.223
2	livestock disease	363	0.028	0.055	0.074
3	bad weather	261	0.102	0.162	0.172
4	flood and livestock disease	532	0.001	0.005	0.008
5	flood and bad weather	457	0.007	0.016	0.019
6	livestock disease and bad weather	558	0.002	0.006	0.010
7	flood, livestock disease and bad weather	695	0.000	0.001	0.001
8	none	1	0.545	0.583	0.234

Table 7: Sum of probabilities of bad states of the world by sub-sample - wave 1				
Sub-ample	median	mean	95% confidence	
<1.25	0.531	0.497	0.471	0.523
>=1.25&<2	0.505	0.470	0.450	0.489
>=2&<3	0.436	0.417	0.397	0.437
>=3	0.323	0.324	0.304	0.344

Table 8: Summary statistics of vulnerability	vulnerability to downside risk (alpha=2)	vulnerability to poverty (alpha=1/3)
# of hh with vuln=0	75	1257
# of hh with vuln!=0	1666	484
median	0.0060	0
mean	0.0151	0.0172
std dev	0.0358	0.0490

Table 9: Vulnerability by wealth in wave 1								
	Vulnerability to poverty				Vulnerability to downside risk			
sub-samples	median	mean	95% confidence		median	mean	95% confidence	
<1.25	0.0962	0.1132	0.1038	0.1226	0.0173	0.0360	0.0291	0.0429
>=1.25&<2	0	0.0023	0.0011	0.0035	0.0026	0.0064	0.0032	0.0097
>=2&<3	0	0.0011	0.0003	0.0019	0.0065	0.0138	0.0114	0.0162
>=3	0	0.0005	0.0002	0.0009	0.0074	0.0147	0.0125	0.0169

Figure 1: Vulnerability to downside risk and consumption in wave 1[19]

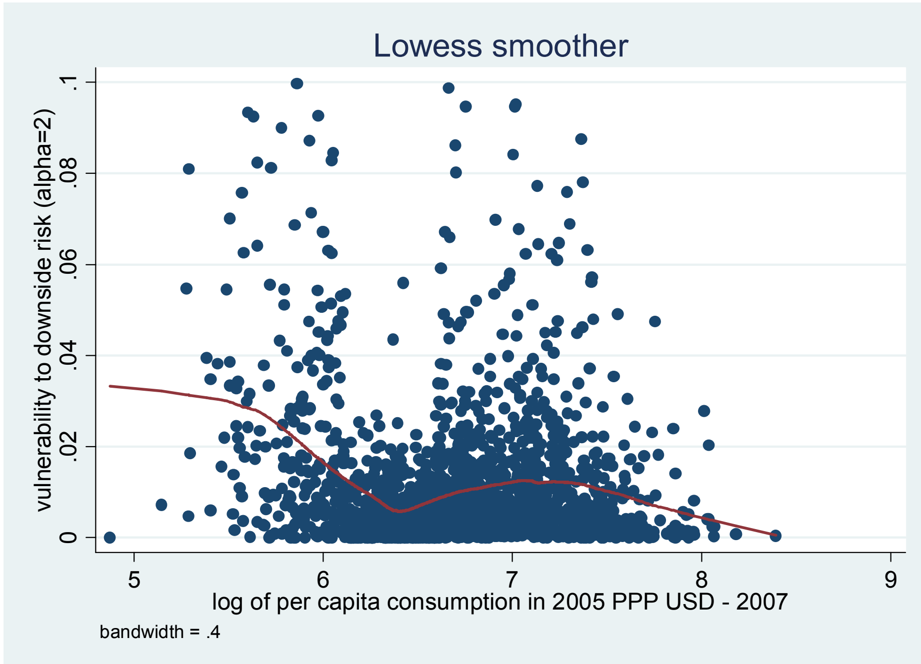
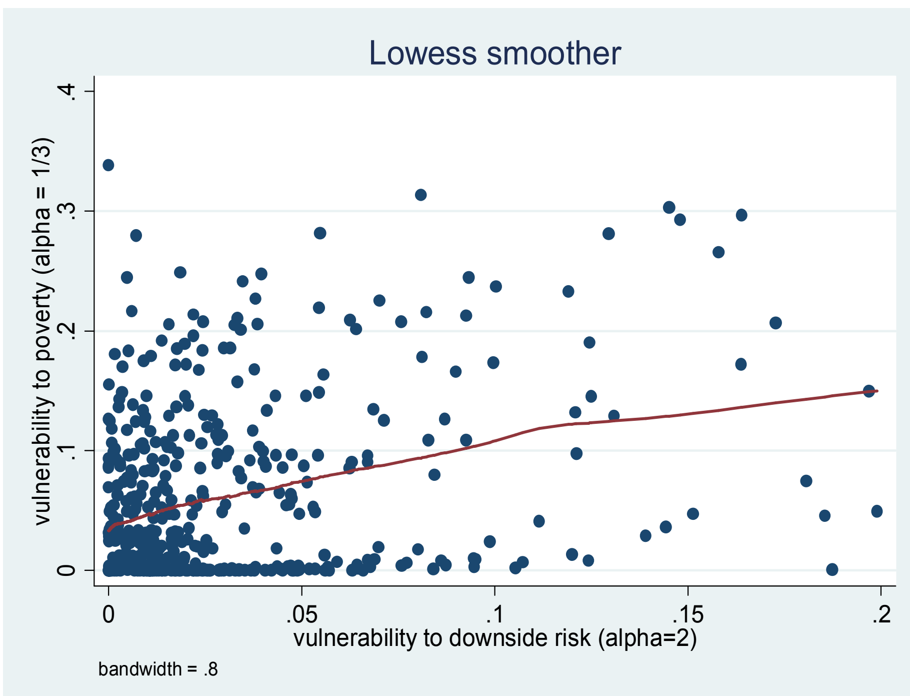


Figure 2: Vulnerability to downside risk versus vulnerability to poverty[20]



[19] Households with vulnerability to downside risk above .1 are excluded.

[20] Households that are not vulnerable to poverty and with a vulnerability to downside risk above .2 are excluded.

Figure 3: Vulnerability to downside risk and consumption change[21]

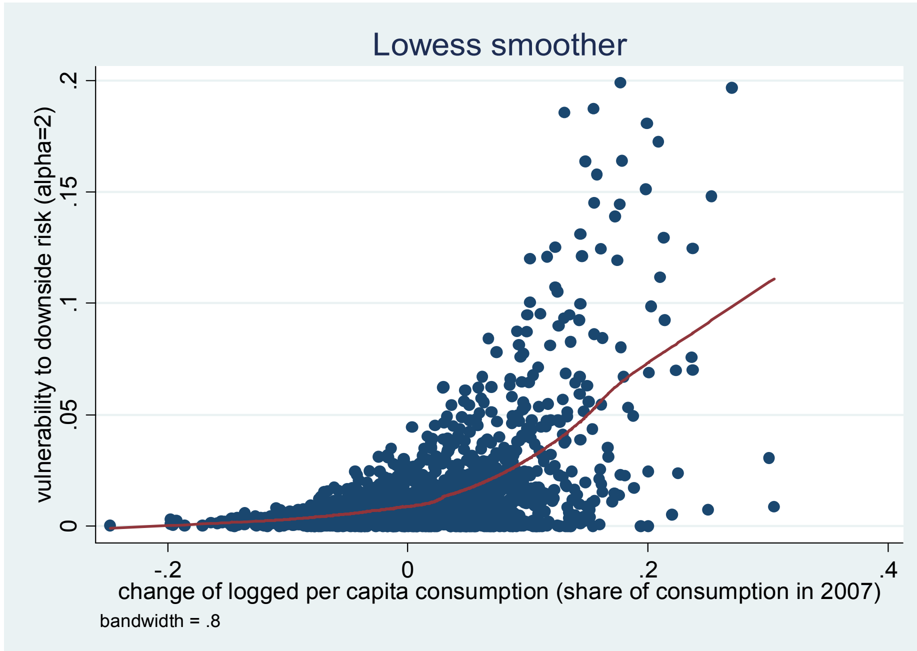
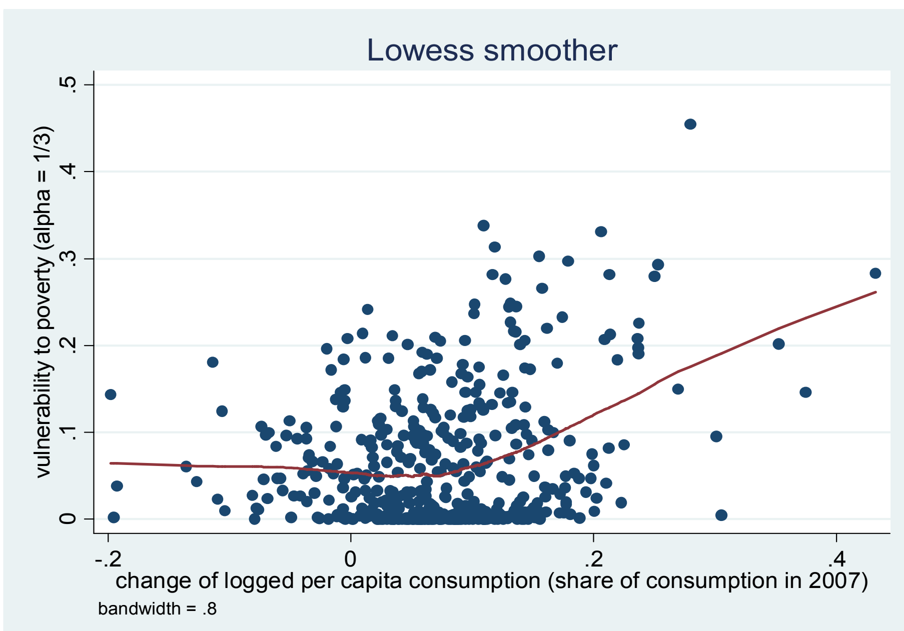


Figure 4: Vulnerability to poverty and consumption change[22]



[21] Households with a vulnerability to downside risk above .2 are excluded.
[22] Households with vulnerability to poverty equal to zero are excluded.

Appendix: Summary statistics of variables		entire sample			extremely poor			moderately but not extremely poor			non poor, non rich			rich		
variable	description	N	mean	std dev	N	Mean	std dev	N	mean	std dev	N	mean	std dev	N	mean	std dev
ln_pc_cpns_w2	log of per capita consumption (in USD PPP 2005; wave 2)	1749	6.876	0.569	248	6.313	0.488	488	6.641	0.434	511	6.957	0.446	502	7.300	0.479
flood	dummy: flood experienced between surveys 1 and 2	1749	0.215		248	0.339		488	0.254		511	0.188		502	0.143	
cr_pest	dummy: crop pest experienced between surveys 1 and 2	1749	0.057		248	0.024		488	0.049		511	0.065		502	0.074	
lst_disease	dummy: livestock disease experienced between surveys 1 and 2	1749	0.071		248	0.060		488	0.076		511	0.074		502	0.070	
bad_weather	dummy: bad weather (storm, heavy rainfall, snow or ice rain) experienced between surveys 1 and 2	1749	0.188		248	0.198		488	0.211		511	0.202		502	0.145	
health	dummy: health shock (illness, accident, death) experienced between surveys 1 and 2	1749	0.101		248	0.077		488	0.109		511	0.096		502	0.110	
w1_hhsize	household size - wave 1	1749	4.404	1.751	248	5.306	1.860	488	4.762	1.741	511	4.264	1.675	502	3.751	1.486
children	number of children in household (<16) - wave 1	1749	1.529	1.310	248	2.246	1.420	488	1.777	1.300	511	1.446	1.259	502	1.020	1.076
elderly	number of elderly in household (>64) - wave 1	1749	0.322	0.610	248	0.391	0.677	488	0.371	0.641	511	0.315	0.611	502	0.247	0.531
hi_some_pr	dummy: highest educational attainment of household member is some primary education - wave 1	1749	0.085		248	0.161		488	0.090		511	0.078		502	0.048	
hi_pr	dummy: highest educational attainment of household member is primary education - wave 1	1749	0.067		248	0.101		488	0.082		511	0.070		502	0.034	
hi_some_lsc	dummy: highest educational attainment of household member is some lower secondary education - wave 1	1749	0.240		248	0.246		488	0.268		511	0.247		502	0.203	
hi_some_usc	dummy: highest educational attainment of household member is some upper secondary education - wave 1	1749	0.081		248	0.056		488	0.068		511	0.057		502	0.129	
hi_usc	dummy: highest educational attainment of household member is some secondary education - wave 1	1749	0.167		248	0.097		488	0.164		511	0.192		502	0.179	

Appendix: Summary statistics of variables - continued		entire sample			extremely poor			moderately but not extremely poor			non poor, non rich			rich		
variable	description	N	mean	std dev	N	mean	std dev	N	mean	std dev	N	mean	std dev	N	mean	std dev
hi_above_sc	dummy: highest educational attainment of household member is above secondary education - wave 1	1749	0.120		248	0.081		488	0.074		511	0.104		502	0.201	
left out category: lower secondary																
hd_age030	dummy: age of household head =<30 - wave 1	1741	0.071		247	0.178		488	0.068		510	0.049		496	0.042	
hd_age3140	dummy: age of household head 31-40 - wave 1	1741	0.256		247	0.304		488	0.291		510	0.255		496	0.200	
hd_age5160	dummy: age of household head 51-60 - wave 1	1741	0.190		247	0.117		488	0.148		510	0.202		496	0.256	
hd_age6170	dummy: age of household head 61-70 - wave 1	1741	0.106		247	0.085		488	0.092		510	0.106		496	0.129	
hd_age71	dummy: age of household head >70 - wave 1	1741	0.075		247	0.085		488	0.086		510	0.075		496	0.058	
left out category: 41-50																
minor	dummy: household head belongs to ethnic minority - wave 1	1741	0.210		247	0.526		488	0.240		510	0.149		496	0.085	
female	dummy: household head is female - wave 1	1741	0.146		247	0.130		488	0.152		510	0.139		496	0.155	
pccons_qnt1_w1	dummy: consumption quintile 1 in wave 1	1749														
pccons_qnt2_w1	dummy: consumption quintile 2 in wave 1	1749														
pccons_qnt3_w1	dummy: consumption quintile 3 in wave 1	1749														
pccons_qnt4_w1	dummy: consumption quintile 4 in wave 1	1749														
left out category: consumption quintile 5																

Bibliography

Amin, S., A. Rai, and G. Topa (2003), Does Microcredit Reach the Poor and Vulnerable? Evidence from Northern Bangladesh. *Journal of Development Economics*, 70(1), 59-82.

Barberis N., M. Huan and R.H. Thaler (2006), Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing. *American Economic Review*, Vol. 96, No. 4, September 2006.

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

Calvo, C. (2008),Vulnerability to Multidimensional Poverty: Peru, 1998-2002. *World Development*, 36(6), 1011-1020.

Calvo, C. and S. Dercon (2007), Chronic Poverty and All That: The Measurement of Poverty over Time. *CSAE Working Paper Series*, WPS/2007-04, Oxford University, Oxford.

Calvo, C. and S. Dercon (2005), Measuring Individual Vulnerability. *Department of Economics Discussion Paper Series*, 229, Oxford University, Oxford.

Chaudhuri, S., J. Jalan, and A. Suryahadi (2002), Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia. Columbia University, *Discussion Paper 0102-52*.

Chetty, R., and A. Looney (2006), Consumption smoothing and the welfare consequences of social insurance in developing economies. *Journal of Public Economics*, 90(12), pp. 2351-2356.

Dercon, S. (2007), Risk and its Consequences in Africa. *GPRG Discussion Paper*, GPRG-WPS-074, Global Poverty Research Group, Oxford.

Elbers, C., and J. Gunning (2003), Growth and Risk: Methodology and Microevidence. *Tinbergen Institute Discussion Papers*, 03-068/2.

Ghaiha, R. and A. Deolalikar (1993), Persistent, Expected and Innate Poverty: Estimates for Semi-arid Rural South India 1975-1984. *Cambridge Journal of Economics*, 17, 409-421

Gaiha, R. and K. Imai (2009), Measuring vulnerability and poverty: Estimates for rural India. Chapter 2 in Naudé and McGillivray (eds.), Vulnerability in developing countries, United Nations University Press.

Günther, I. and J. Maier (2008), Individual Vulnerability and Loss Aversion, draft.

Halvorsen, R., and R. Palmquist (1980), The interpretation of dummy variables in semilogarithmic equations. American Economic Review, 70, pp.474-475.

Harding, R. (ed) (1998), Environmental decision-making: the roles of scientists, engineers and the public. The Federation Press: Sydney.

Hoddinott, J. and A. Quisumbing (2003), Methods for Microeconometric Risk and Vulnerability Assessments. *Social Protection Discussion Paper 0324*, The World Bank, Washington D.C.

Jalan, J. and M. Ravallion (1998), Transient Poverty in Postreform China. *Journal of Comparative Economics*, 26, 338-357.

Kamanou, G., and J. Morduch (2004), Measuring Vulnerability to Poverty. Chapter in Dercon, S. (ed.), Insurance against Poverty, Oxford University Press.

Ligon E., and S. Schechter (2004), Evaluating Different Approaches to Estimating Vulnerability. *Social Protection Discussion Paper 0410*, The World Bank, Washington D.C.

Ligon E., and S. Schechter (2003), Measuring vulnerability, *Economic Journal*, 113: 95-102.

Pritchett, L., Suryahadi, A. and S. Sumarto (2000), Quantifying Vulnerability to Poverty: A Proposed Measure, with Application to Indonesia. *SMERU Working Paper*, The World Bank, Washington D.C.

Townsend, R. (1994), Risk and Insurance in Village India. *Econometrica*, Vol. 62, No. 3, pp. 539-591.

Wagstaff, A., and M. Lindelow (2010), Are Health Shocks Different? Evidence from a Multi-Shock Survey in Laos. Development Research Group, WPS 5335, The World Bank, Washington DC.

World Bank (2001), World Development Report 2000/2001 – Attacking Poverty. New York, Oxford University Press.