

METHODS FOR MICROECONOMETRIC RISK AND VULNERABILITY ASSESSMENTS

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1. INTRODUCTION

The increasing recognition that there are considerable flows into and out of poverty (Baulch and Hoddinott 2000) has focused interest in household vulnerability as the basis for a social protection strategy. However, the design and implementation of these schemes is hampered by uncertainty over the meaning of this concept. Vulnerability—like risk and love—means different things to different people; there are many definitions of vulnerability and, seemingly, no consensus on its definition or measurement. One might be forgiven for thinking that the discourse on vulnerability is too confused to support initiatives in the areas of policy and interventions.

Such a view is too strong: there are commonalities across myriad definitions and methodologies. Specifically, all focus on the measurement of welfare in a world in which welfare reflects, in part, the interplay between the realization of stochastic events or shocks and individual's or household's or community's or country's ability to anticipate and respond to such events. Assessments of vulnerability are particularly concerned with downside risks, those that cause welfare to fall. Although they typically express welfare in terms of consumption, and the norm or benchmark as the poverty line, vulnerability is a sufficiently general concept that encompasses many dimensions of well-being. Vulnerability can be assessed at the individual or household level; it can also be aggregated over these units of observation.

This chapter summarizes the currently available quantitative tools that measure vulnerability. It reviews data options currently available to researchers and how these can be supplemented with other sources in order to conduct risk and vulnerability assessments. While one could use price, exchange rate, and balance of payments data to examine macroeconomic shocks, and rainfall data to assess the severity of droughts and floods, we are ultimately interested in their impacts on households—thus the emphasis on household data. It is divided into four principal sections. Section 2 provides a conceptual framework that links risk, risk management, and vulnerability. Section 3 builds on this discussion to describe techniques for measuring vulnerability within a population. Section 4 discusses the data issues associated with their implementation. Building on these discussions, Section 5 focuses on four questions: (1) Who is vulnerable? (2) What are the sources of vulnerability? (3) How do households cope with risk and vulnerability? and (4) What is the gap between risks and risk management mechanisms? Section 6 concludes.

2. RISK, RESOURCES, AND VULNERABILITY: A CONCEPTUAL FRAMEWORK

Our first step is to link the sources of risk that households face, the resources and the risk management techniques available to them, and vulnerability—the “risk chain.”¹ To provide a framework for understanding the “risk chain,” we propose a conceptual framework grounded in three components: “settings,” “assets,” and “activities.”² *Settings* describe the environment in which a household resides. All *assets* share a common characteristic, namely that alone or in conjunction with other assets, they produce a stream of income over a period of time. Some assets have a second characteristic, namely that they are a store of value. The allocation of these assets to income-generating *activities* is conditioned by the settings in which these households find themselves. The outcome of these allocations is income, which is a determinant of consumption, poverty, and vulnerability.

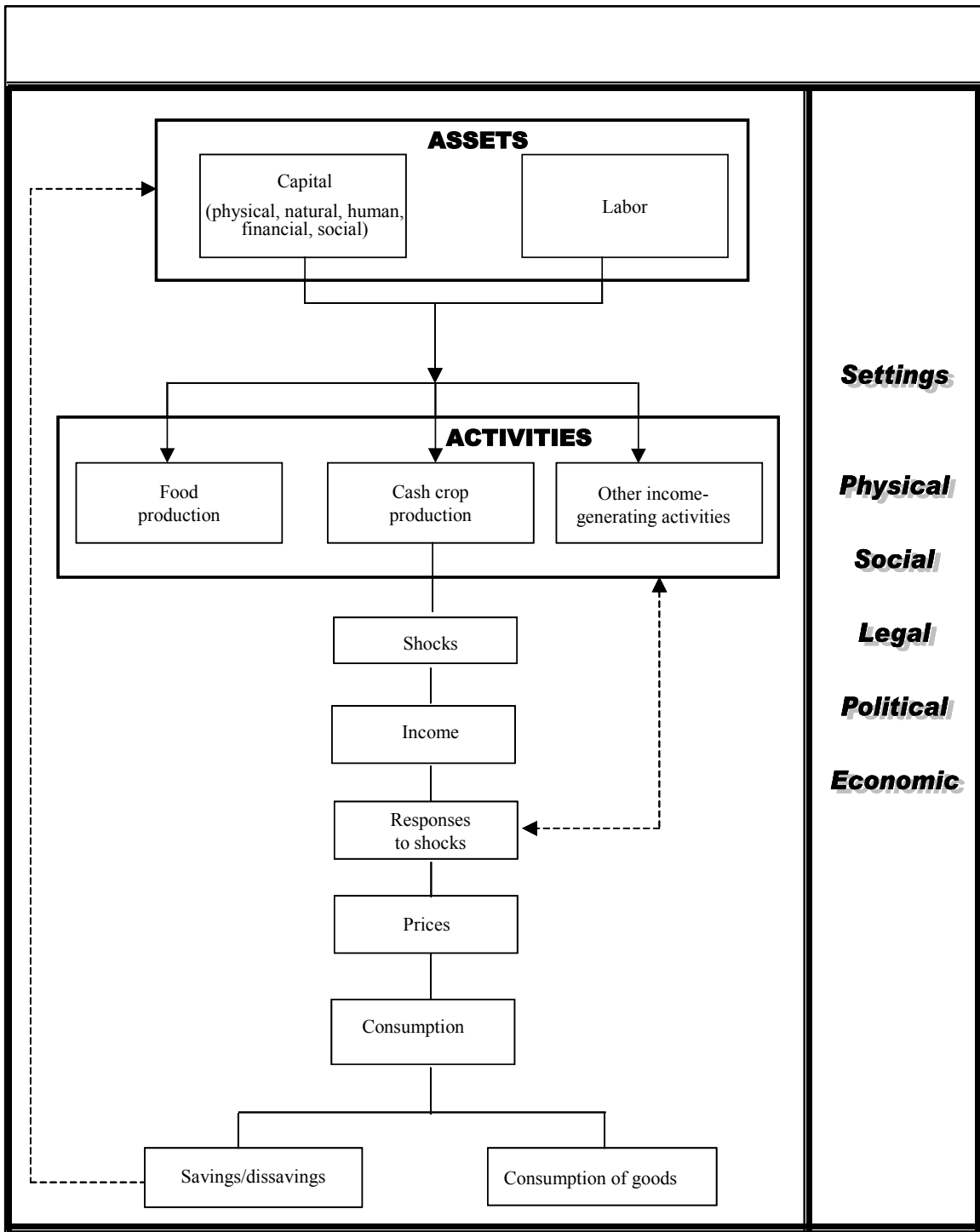
Consider a household residing in a rural locality. This locality is characterized by a single growing season, followed by a period of time in which no crops are cultivated.³ As shown in Figure 1, this household exists within five settings: physical, social, political, legal, and economic. The physical setting refers to natural phenomena such as the level and variability of rainfall, the natural fertility of soils, distances to markets, and quality of infrastructure. The social setting captures such factors as the existence of certain norms of behavior, of social cohesion and strife. The legal setting can be thought of as the general “rules of the game” in which exchange takes place, which, in turn, is partly a function of the political setting that captures the mechanisms by which these rules are set. Finally, there is an economic setting that captures policies that affect the level, returns, and variability of returns on assets. Within these settings, the household has endowments of capital and labor. Capital includes physical capital (agricultural tools, livestock), natural capital (land), human capital (in the form of knowledge, skills, and health), financial capital (cash-in-hand, bank accounts, net loans outstanding), and social capital (networks, norms, and social trust that facilitates coordination and cooperation). Labor endowments reflect the household’s ability to work either for itself or external employers. Holding assets is a key *ex ante* risk management mechanism.

¹ See Holzmann (2001) and Holzmann and Jørgensen (2000). Rather than making repeated references, we note that our discussion draws on these papers as well as Dercon (2001), Heitzmann, Canagarajah, and Siegel (2002), and Moser (1998).

² This framework draws on ideas developed in Baulch and Hoddinott (2000), Deaton (1992), Dercon (2001, 2002), Hoddinott, Haddad, and Mukherjee (2000), Hoddinott and Quisumbing (2003a, 2003b), and Hoddinott (2006). It bears some similarities to the sustainable livelihoods framework; see DfID (1997) and Carney et al. (1999).

³ These assumptions are made solely for simplicity; allowing multiple growing seasons would not change the framework that follows in any substantive way.

Figure 1. Conceptual framework: Settings, assets, and activities



The household allocates these endowments across a number of activities. In Figure 1, these activities are food crops, cash crops, and other income-generating activities, but these are solely for illustration. They could just as easily be disaggregated into, say, agricultural and nonagricultural activities, or disaggregated further by crop and livestock type. These allocations are based on the household's perception of the level of returns to these activities as well as the variability of returns and their covariance. Similarly, the household might diversify into off-farm activities (such as handicrafts or processing) or casual wage labor.⁴

The relationship between endowments, activity choice, and income is affected by the likelihood of a shock occurring, what Heitzmann, Canagarajah, and Siegel (2002) call a "risk realization." These could be shocks that emanate from the setting in which households are situated—a common or covariant shock—or they could be restricted to only this household, an idiosyncratic shock. The distinction between covariant and idiosyncratic shocks is not always clear-cut. A drought in only one locality might result in poor, rainfall-dependent households selling assets to richer, non-rainfall dependent households so, although the event was common to both, it adversely affected only the poor. Table 1, taken from Dercon, Hoddinott, and Woldehanna (2005), shows how some shocks have widespread effects while others are household specific.

Table 1. Extent of shocks, by selected shocks, Ethiopia

	Households reporting this shock	How widespread was this shock?				
		Only affected this household	Affected some households in this village	Affected all households in this village	Affected this village and nearby villages	Affected areas beyond this <i>kebele</i>
		Idiosyncratic	←----- covariate ----->			
Drought	52%	6%	15%	32%	26%	21%
Pests or diseases affecting crops or livestock	38	20	29	25	18	8
Input shocks (price increase or difficulties in access)	35	13	18	27	23	18
Output shocks (price decrease or difficulty making sales)	29	6	12	36	33	14
Victim of theft or other crime	22	77	14	4	3	1
Death of husband, wife or another person	35	80	10	5	4	1
Illness of husband, wife or another person	39	83	9	5	3	0

Source: Data are taken from the Ethiopian Rural Household Survey, Round 6; 1,368 households provided reported information, Dercon, Hoddinott, and Woldehanna (2005).

⁴ Alderman and Paxson (1992), Baulch and Hoddinott (2000), McCloskey (1976), Morduch (1990, 1995, 1999), and Townsend (1995) discuss these mechanisms further.

The allocation of endowments to activities, together with returns to endowments in these activities, generates income.⁵ However, it is unlikely that there is a one-to-one relationship between income and consumption. Households engage in ex post risk management; for example, they may alter the amount of labor they supply to the labor market (Kochar 1999). They may draw down savings held in financial form, as livestock, as jewelry or other durables. Alternatively, they may enter the credit market and borrow. They may alter investment in human capital.⁶ They may attempt to gain access to resources from the state or they may draw on private sources, such as remittances or gifts. Accordingly, household consumption, and thus vulnerability, depends on the nature of the shock, the availability of additional sources of income, the functioning of labor, credit and insurance markets, and the extent of public assistance. As shown in Figure 1, some ex post responses generate the feedback mechanisms from consumption decisions to changes in asset holdings.

Several caveats should be noted. First, for purposes of exposition, we have presented mechanisms for consumption smoothing as ex post responses to shocks. In practice, decisions regarding consumption are interlinked to decisions regarding income generation and perceptions of risk.⁷ Second, our conceptual framework treats the external environment as exogenous. Although this may be appropriate as a short-run assumption, one could argue that over the longer term the external environment can be altered by actions by the household (for example, where households lobby governments for resources, or deforestation results from unsustainable forest use). Third, an unattractive feature of this framework is that it treats the household as a single undifferentiated unit despite much evidence questioning this assumption (Alderman et al. 1995). However, it is relatively straightforward to make it gender, and generational, sensitive; Hoddinott (2008) and Hoddinott (2006) provide an empirical example showing how a covariate shock had gender and age differentiated effects.

Covariate shocks are events resulting from changes in settings. Table 2 provides examples,⁸ focusing on two key elements needed to characterize them: the setting in

⁵ Some households may allocate assets to activities that may not generate income immediately, but may have a return at some point in the future. Investments in social relations or covering the costs of the migration of a family member are examples of this.

⁶ Jacoby and Skoufias (1997) note that adverse income shocks cause households to reduce the schooling of girls in semi-arid India.

⁷ Fafchamps (1993) provides a good example of how labor allocation decisions evolve in semi-arid Burkina Faso as the extent of rainfall shocks becomes known. If rainfall is better than expected, farmers devote additional time to weeding crops. But if rainfall shocks are negative, labor is reallocated out of agriculture and into other, more remunerative activities.

⁸ Table 2 expands upon ideas found in Dercon (2001), Heitzmann, Canagarajah, and Siegel (2002), and Hoddinott and Quisumbing (2003a).

which the shock takes place, and the speed of onset and duration of the shock itself.⁹ These shocks can affect any or all of the components of our conceptual framework: settings, household assets, or the processes by which these assets are used to generate income. These effects can take place in multiple rounds: a shock taking place in one setting can have impacts on other settings, unleashing additional effects on household assets and the processes by which households generate income and then turn that income into consumption. Tables 3 and 4 provide selected examples.

Table 2. Shocks, their speed of onset, and their duration

Setting in which the shock takes place	Speed of onset/Duration of the shock		
	Rapid onset	Slow onset	Prolonged
Physical	- Heavy rains; flooding - Landslides - Volcanic eruptions - Earthquakes - Hurricanes - Insect infestations (e.g., locusts)	- Drought - Epidemics	
Social	- Sudden forced relocation or resettlement	- Breakdown in traditional commitments of trust and reciprocity	- Ethnic strife - Civil war
Political	- Riots - Coup d'etat		- Collapse of governance
Legal		- Changes in legal environment eroding or eliminating tenure security or title to property	
Economic	- Inflation, stock market or exchange rate collapse leading to loss of value of financial assets	- Loss of export markets - Collapse in prices of internationally traded agricultural commodities	- Changes in fundamental structure of the economy (e.g., transition from centrally planned to mixed or market economy)

Table 3. Examples of impact of selected shocks on settings

Shock	Setting in which shock takes place/Impacts on that setting	Possible impacts on other settings
Floods, landslides, earthquakes, hurricanes	Physical: Destruction of public physical infrastructure (roads, bridges, clinics, water systems, etc.)	Economic: increased prices of food and other goods Social: breakdown of social cohesion if recovery is not rapid
Drought	Physical: Reduced soil moisture for plant growth; possibly reduced surface or ground water for drinking	Economic: increased prices, reduced availability of food; possible decisions by government to limit food trade
Ethnic strife	Social: Reduced social cohesion, increased violence	Political: More authoritarian government Legal: More restrictive laws; less personal freedom Physical: Destruction of public infrastructure Economic: Increased prices

⁹ Strictly speaking, speed of onset and duration of the shock are two different concepts. A flood can be rapid-onset, but can also submerge productive land for a long period of time. An epidemic can spread slowly but end relatively quickly if the virus mutates or if public health responses are mobilized in a timely fashion.

Table 4. Examples of impact of selected shocks on household assets and transformation processes

Shock	Impact on household assets	Impact on activities and outcomes	
		Availability of and returns to income earning activities	Availability and real costs of transactions
Floods, landslides, earthquakes, hurricanes	<ul style="list-style-type: none"> • Damage or destruction of productive and other household assets 	<ul style="list-style-type: none"> • General reduction in wage labor and other off-farm opportunities • Reduced access to agricultural inputs; inability to sell agricultural surplus 	<ul style="list-style-type: none"> • Increase real costs of food and other goods consumed by the household • Some goods either unavailable or rationed • Difficulty in accessing publicly provided goods such as schools and health
Drought	<ul style="list-style-type: none"> • Livestock death 	<ul style="list-style-type: none"> • Reductions in returns to labor and other inputs in agriculture • Fewer wage labor opportunities in agriculture 	<ul style="list-style-type: none"> • Increased real costs of food; staples may be unavailable
Ethnic strife, crime	<ul style="list-style-type: none"> • Temporary/permanent confiscation of physical assets • Loss of labor through abduction, conscription or imprisonment • Forced relocation 	<ul style="list-style-type: none"> • Reduced access to agricultural inputs; difficulty selling agricultural surplus • Reductions in returns due to insecurity, lower output prices • Reduced hiring of agricultural labor 	<ul style="list-style-type: none"> • Increases real costs of food and other goods consumed by the household • Some goods either unavailable or rationed • Difficulty in accessing publicly provided goods such as schools and health

The immediate impacts of a shock on settings, and the related impact on household assets, activities, and outcomes may or may not threaten human life or risk creating irreversibilities. Whether such consequences occur depends on six factors: the magnitude of these impacts, the speed of onset of the shock, the duration of the shock, households' pre-shock food security status, responses to these events, and secular trends in this status. We use Figures 2 to 6 to illustrate the joint role played by these factors where the welfare indicator is household food security. The vertical axis represents some measure of household food security with a threshold level being denoted by a horizontal food security line. The horizontal axis is time, measured in years. Each of these figures differs, however, in terms of the time path of the food security outcome observed for a single household in the absence of an external response.

Figure 2 represents a rapid onset shock affecting a household with pre-shock food security well above the minimum threshold. The shock causes food consumption to fall, but not so far as to be life-threatening. Further, the shock does not have irreversible effects as seen by the fact that over time, the pre-shock level of food consumption is resumed. While a response to this shock would be beneficial in terms of mitigating the short-term costs of the event, they are not essential in terms of either saving lives or preventing irreversibilities. Figure 3 represents a slow onset shock, as shown by the slower decline in household food security. The magnitude of the shock is sufficiently large so as to imperil life and so a public response is needed. And while the household does recover from this shock, recovery takes time. Figure 4 is a variant on Figure 3; the

principal difference being that, post-shock, household per capita food consumption (or whatever measure of food security being used) never reaches its previous level; this shock has led to some irreversibility. In this circumstance, a larger (and arguably) longer response is needed.

Figure 2. A shock with short-term transitory consequences

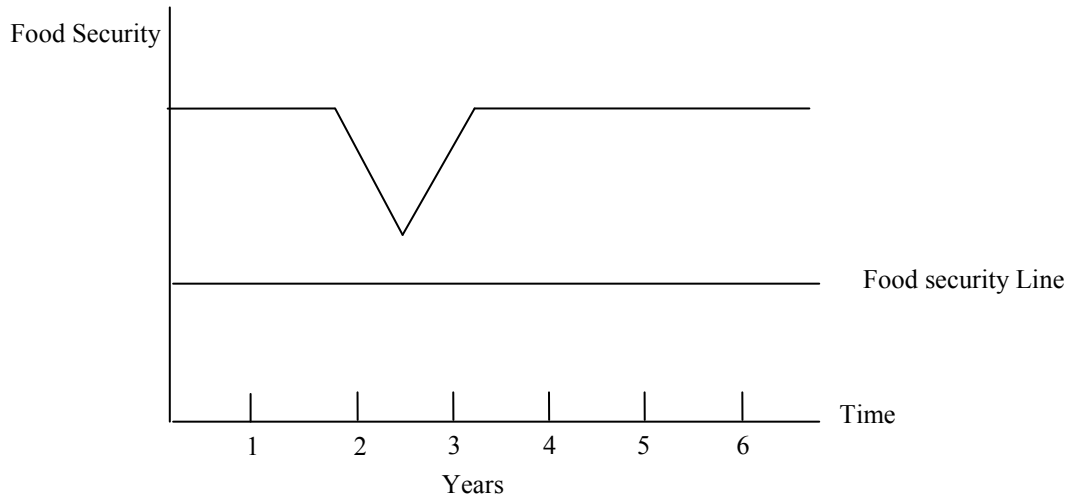


Figure 3. A transitory shock with life-threatening consequences

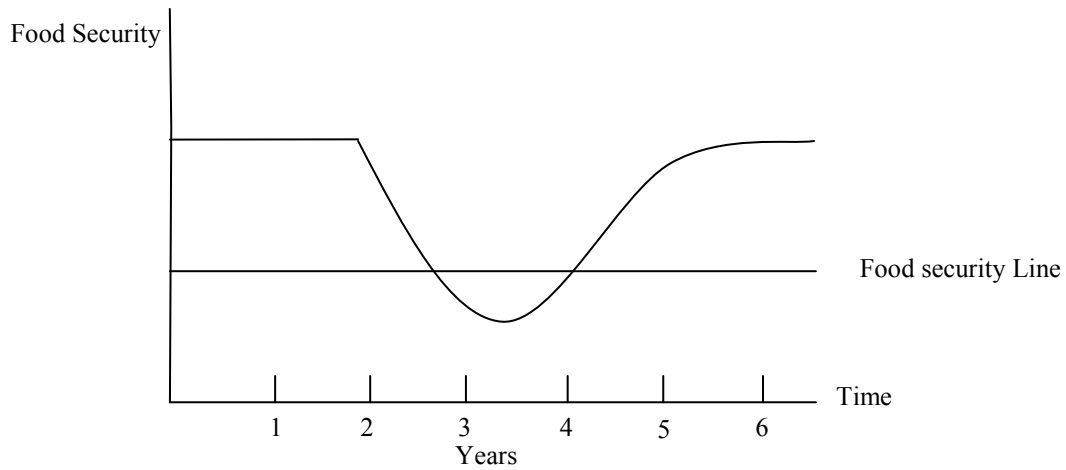


Figure 4. A transitory shock with life-threatening consequences and permanent consequences

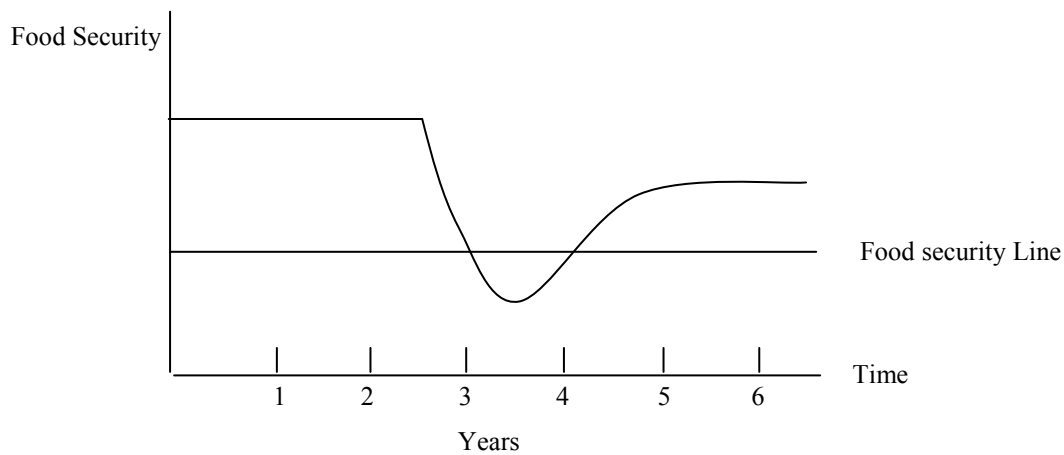


Figure 5 represents a case of cascading shocks. The first shock causes food consumption to fall but not quite to a level that threatens life. However, this shock is followed by a second shock soon afterward and the combined effect is large enough to push households below the minimum food security line and to produce irreversible consequences. Shocks such as these are potentially quite difficult to assess, as the magnitude of the initial shock might not seem large enough to justify a response. The second shock pushes the household below the food security threshold in part because it follows a previous event that did not trigger assistance. This case of cascading shocks highlights the feedback between the adequacy of public responses and households' ability to withstand future shocks. Finally, Figure 6 presents an especially dire picture. The secular trend in food security is downward and the shock accelerates this downward trend. In this case, responses need to go beyond those necessary to save human life; failing to address the irreversibilities that exist as a result of this adverse event will require assistance on a continuous basis.

Figure 5. A cascading series of shocks

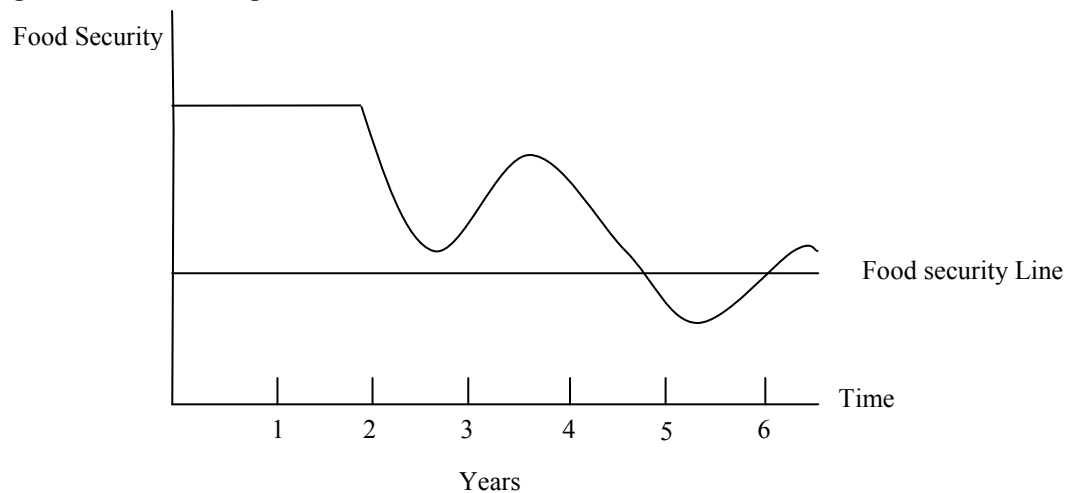
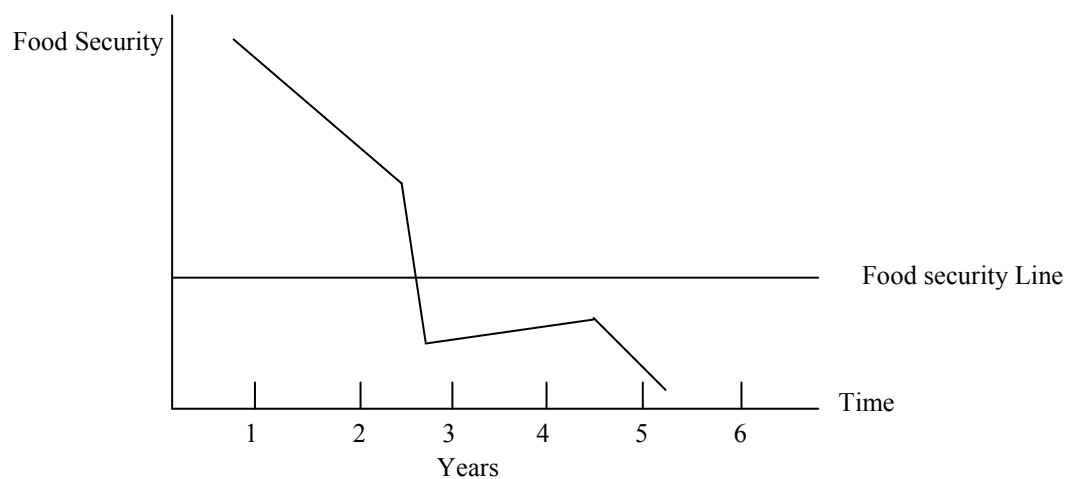


Figure 6. A shock that accelerates a downward trend



3. QUANTITATIVE CONCEPTS OF VULNERABILITY

Our conceptual framework incorporates sources of risk, resources available to households, and risk management techniques. The interplay between these components was reflected in outcomes such as consumption and food security. Implicit in this framework are elements that appear in the literature on vulnerability such as exposure to shocks, household responses to such events, and the links between transitory events and permanent consequences. In this section, we formalize these links by providing an overview of quantitative concepts of vulnerability.

3.1 Overview

Vulnerability is the likelihood that at a given time in the future, an individual will have a level of welfare below some norm or benchmark. The time horizon and welfare

measure are general. One could think of vulnerability pertaining to the likelihood of being poor next year, in ten years time, or being poor in old age. Although vulnerability is typically expressed in terms of consumption, and the norm or benchmark as the poverty line, the definition of vulnerability is sufficiently general so as to encompass many dimensions of well-being. Vulnerability can be assessed at the individual or household level; it can also be aggregated over these units of observation.

Concepts of vulnerability and poverty are linked but are not identical. Chaudhuri, Jalan, and Suryahadi (2002) write:

Vulnerability is an *ex ante* (forward-looking) rather than an *ex post* concept. Poverty status can be observed at a specific time period, given the welfare measure and the poverty threshold. By contrast, household vulnerability is not directly observed, rather it can only be predicted. . . . Poverty and vulnerability (to poverty) are two sides of the same coin. The observed poverty status of a household . . . is the ex-post realization of a state, the ex-ante probability of which can be taken to be the household's level of vulnerability.

As an example, consider Figures 7 and 8. The horizontal axis in Figure 7 represents predicted or expected levels of consumption at some point in the future, $t + 1$; the vertical axis, the proportion of households with that expected level of consumption. Households also differ in their exposure to shocks and their ability to cope with these shocks. In Figure 7, expected (mean) levels of consumption are denoted by the filled rectangles. Possible realizations of consumption, depending on the state of the world around these mean levels, are shown by the horizontal rule that passes through these rectangles; they can be thought of as confidence intervals. There is no reason why such a distribution must be symmetric and so some rules have longer left (right) tails than others. Some groups of households may be more vulnerable to shocks than others (for example, they may live in localities more prone to natural disasters or their livelihoods depend on commodities with especially volatile prices) or have less ability to manage these shocks; such groups are characterized by having longer leftward-lying horizontal rules. Last, Figure 7 includes a vertical line denoting the level at which expected consumption exceeds the poverty line. Thus, Figure 7 conveys four pieces of information: expectations about consumption (the filled rectangles); possible states of the world around that expectation (the horizontal rule); the location of that distribution relative to the poverty line; and the proportion of households characterized by that expected value and possible states. When $t + 1$ arrives, some shocks occur, others do not and the outcome of that, together with the factors that affect mean consumption levels, yields a distribution of consumption such as that depicted in Figure 8. The proportion of households lying to the left of the vertical rule is the familiar headcount measure of poverty.

Figure 7. Expected levels of consumption, $t + 1$

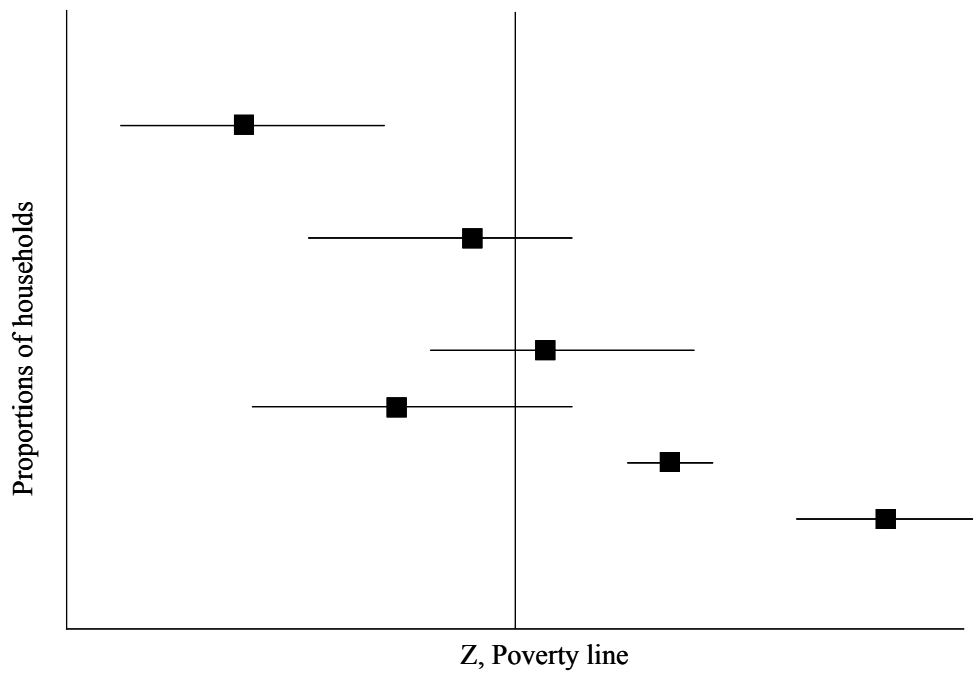
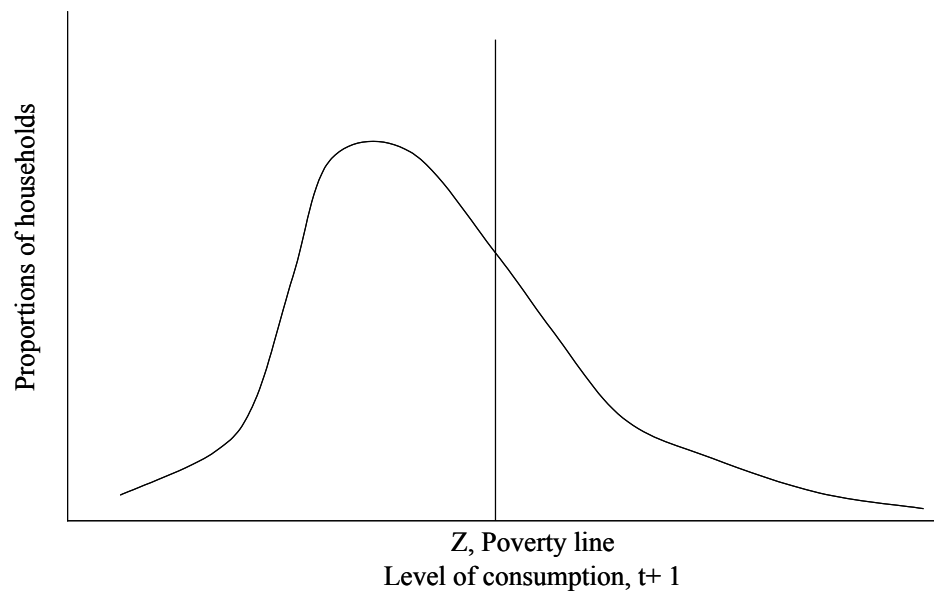


Figure 8. Realized distribution of consumption, $t + 1$



There are three principal approaches to assessing vulnerability: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), and vulnerability as uninsured exposure to risk (VER). All share a common characteristic, namely they construct a model that predicts a measure of welfare. VEP and VEU share two further commonalities; they make reference to a benchmark for this welfare indicator, z , and enumerate a probability of falling below this benchmark, p . Denoting vulnerability of household h as V_h , and the welfare measure as y , both defined vulnerability as $V_h(y_h, z, p_h)$; put crudely, vulnerability is the likelihood that realized consumption—where a household ends up along its horizontal rule in Figure 7—lies to the left of the vertical rule. VEP and VEU approaches measure vulnerability at the individual level; summing over all individuals or households gives a measure of aggregate vulnerability. VER do not measure vulnerability because they do not construct probabilities; instead, they assess whether observed shocks generate welfare losses. They are ex post assessments of the extent to which a negative shock causes a household to deviate from expected welfare, measuring the length of the rule to the left of the expected level of welfare.

3.2 Vulnerability as Expected Poverty (VEP)

Chaudhuri, Jalan, and Suryahadi (2002) and Christiaensen and Subbarao (2001) provide examples where vulnerability is defined as the probability that a household will fall into poverty in the future. They define welfare in terms of consumption so that vulnerability of household h at time $t - V_{ht}$ is the *probability* that the household's level of consumption at time $t + 1$ (c_{ht+1}) will be below the consumption poverty line, z :

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

Pritchett, Suryahadi, and Sumarto (2000) extend this time horizon, noting that since the future is uncertain, the degree of vulnerability rises 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 is one minus the probability of no episodes of poverty:

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

Denoting $I[\bullet]$ as an indicator equaling one if the condition is true, zero otherwise, Pritchett, Suryahadi, and Sumarto (2000) define a household as vulnerable if the risk in n periods is greater than a threshold probability p :

$$V_{ht}(p, n, z) = I\{R_{ht}(n, z) > p\}. \quad (3)$$

Neither (1) nor (3) explicitly take into account the depth of expected poverty. Consider two households both of whom are vulnerable—we know with certainty that both will be poor in period $t + 1$. Suppose that we were to transfer sufficient consumption from one household to the other such that the recipient household will not be poor in period $t + 1$. According to a headcount measure, we have reduced vulnerability by making a poor household even poorer. This is relatively straightforward to redress. One can rewrite equation (1) as

$$V_{ht} = \sum_s p_s \cdot P(c_{h,t+1}, z) = \sum_s p_s \cdot I[c_{h,t+1} \leq z] \cdot [(z - c_{h,t+1})/z]^\alpha, \quad (1')$$

where $\sum_s p_s$ is the sum of the probability of all possible “states of the world,” s in period $t + 1$ and α is the welfare weight attached to the gap between the benchmark and the welfare measure. Chaudhuri, Jalan, and Suryahadi (2002) and Christiaensen and Subbarao (2001) set α equal to 0 but there is no reason why it could not be specified in terms of $\alpha = 1, \alpha = 2$, etc.¹⁰

Estimating the probability of expected poverty ($V_{ht} = Pr(c_{h,t+1} \leq z)$, equation (1) requires an estimate of the *distribution* of consumption for household h , an assumption regarding the benchmark or threshold level below which the household is considered poor and an assumption regarding the threshold probability at or above which a household is considered vulnerable. Given a lengthy time series, one could use observed distributions of consumption.¹¹ Chaudhuri, and Christiaensen, and their co-authors show how such distributions can be uncovered with access to only a single cross section. Assume that consumption is determined by the following stochastic process:

$$\ln c_{ht} = \beta \mathbf{X}_h + e_h, \quad (4)$$

where $\ln c_{ht}$ is log consumption, \mathbf{X}_h is a vector of household characteristics (e.g., location, characteristics of head, assets, prices, shocks), β is a vector of parameters to be estimated, and e_h is a disturbance term with mean zero.¹² The variance of the disturbance term (σ_{eh}^2) is

$$\sigma_{eh}^2 = \tau \mathbf{X}_h, \quad (5)$$

¹⁰ While these measures of vulnerability as expected poverty are defined for individual households, they can be aggregated over N households just as one constructs a headcount or P2 poverty measure. To do so, write $VEP_t = (1/N) \sum_h \sum_s p_s \cdot I[c_{h,t+1} \leq z] \cdot [(z - c_{h,t+1})/z]^\alpha$.

¹¹ If consumption follows an autoregressive process of low order, a shorter time series – say two or three observations – would suffice. We thank an anonymous reviewer for bringing this observation to our attention.

¹² A concern in regressions such as these is that some of these right-hand-side terms, such as assets, are themselves affected by shocks and as such, are endogenous.

where τ is also a vector of parameters. These, together with \mathbf{X}_h , can be used to calculate expected log consumption and the variance of log consumption:

$$E[\ln c_{ht} | \mathbf{X}_h] = \mathbf{X}_h \beta_{hat} \quad (6)$$

and

$$\text{Var}[\ln c_{ht} | \mathbf{X}_h] = \sigma_{ehhat}^2 = \mathbf{X}_h \tau_{hat}. \quad (7)$$

Chaudhuri assumes that consumption is log normally distributed. Once the consumption poverty threshold, z , is determined and a threshold probability value above which a household is considered vulnerable established (most studies set this at 0.5), the probability that a household with characteristics \mathbf{X}_h will be poor is given by

$$v_{ht} = Pr(\ln c_h < \ln z | \mathbf{X}_h) = \Phi[(\ln z - \mathbf{X}_h \beta_{hat}) / \sqrt{\mathbf{X}_h \tau_{hat}}]. \quad (8)$$

This approach assumes that cross-sectional variability is a good proxy for intertemporal variation. In addition to this assumption, (1) a strong homogeneity assumption must be made in order to interpret results of vulnerability, namely that all households observed in the cross-section receive draws from the same distribution of consumption changes. While one can refine this measure by disaggregating by region, income group, etc., the assumption of homogeneity still has to be made; and (2) in using the standard deviation as a measure of vulnerability, downside risk is weighed the same as upside risk. For these reasons, Kamanou and Morduch (2002) adopt a different approach in estimating their measure of vulnerability, generating a distribution of possible future outcomes for households using bootstrap techniques, based on their observed characteristics and consumption fluctuations of “similar” households.

3.3 Vulnerability as Low Expected Utility (VEU)

Vulnerability as expected poverty measures can generate some odd results. Consider two scenarios. In the first, a risk-averse household is certain that expected consumption in period $t + 1$ is just below the poverty line so that the probability of poverty (i.e., vulnerability) is one. In the second scenario, we introduce a small mean preserving spread such that while mean expected consumption remains unchanged, there is probability 0.5 that the household will have consumption just above the poverty line (and above the mean) and probability 0.5 that the household will have consumption slightly lower than the mean. Moving from the first scenario to the second makes the household worse off (being risk-averse, it would prefer the certain consumption to the

expected consumption) while reducing vulnerability, from 1 to 0.5. Using this measure, a policymaker seeking to reduce vulnerability should introduce new risks or remove insurance!

Ligon and Schechter (2002, 2003) propose a measure of vulnerability that redresses this weakness. They define vulnerability with reference to the difference between the utility derived from some level of certainty-equivalent consumption, z_{CE} at and above which the household would not be considered vulnerable— z_{CE} is analogous to a poverty line—and the expected utility of consumption. As in Figure 7 and the measures of vulnerability as expected poverty, consumption of household, c_h , has a distribution that reflects different states of the world. They write their measure of vulnerability as

$$V_h = U_h(z_{CE}) - EU_h(c_h), \quad (9)$$

where U_h is a weakly concave, strictly increasing function. Equation (9) can be rewritten as

$$V_h = [U_h(z_{CE}) - U_h(Ec_h)] + [U_h(Ec_h) - EU_h(c_h)]. \quad (10)$$

The first bracketed term is the difference in utility at z_{CE} compared to household h 's expected consumption at c . The second term measures the risk faced by household h . It can be decomposed into covariate or aggregate and idiosyncratic risk. Let $E(c_h|\mathbf{x}_t)$ be the expected value of consumption, conditional on a vector of covariant variables \mathbf{x}_t and so we rewrite (10) as

$$\begin{aligned} V_h &= [U_h(z_{CE}) - U_h(Ec_h)] && \text{(Poverty)} \\ &+ \{U_h(Ec_h) - EU_h[E(c_h|\mathbf{x}_t)]\} && \text{(Covariate or Aggregate risk)} \\ &+ \{E U_h[E(c_h|\mathbf{x}_t)] - EU_h(c_h)\} && \text{(Idiosyncratic risk)}. \end{aligned} \quad (11)$$

Estimating (11) requires choosing a functional form for U_h and devising a way of estimating the conditional expectations, $E(c_h|\mathbf{x}_t)$. Ligon and Schechter (2003) suggest the following:

$$U_h = (c^{1-\tau}) / (1-\tau),$$

where $\tau > 0$. τ is the household coefficient on relative risk aversion; the existing empirical literature suggests that $\tau = 2$ is a good approximation of this measure. With respect to the conditional expectation, Ligon and Schechter (2003) use a variant of equation (11):

$$E(c_h|\mathbf{x}_t) = \alpha_h + \eta_t + \delta X_{hvt}, \quad (12)$$

where α_h are household fixed effects (restricted to sum to zero), c_h is normalized so that average equals one, and η_t are covariate or aggregate effects. That is, \mathbf{x}_t is decomposed into two parts, covariate (\mathbf{x}_{vt})—as captured by η_t —and household specific (\mathbf{x}_{hvt})—as captured by $\eta_t + \delta X_{hvt}$. They also note that measurement error will be conflated with their estimate of idiosyncratic risk so they calculate the following:

$$\begin{aligned} V_h = [& U_h(Ec) - U_h(Ec_{ht}) && \text{(poverty)} \\ & + \{U_h(Ec_{ht}) - EU_h[E(c_{ht}|\mathbf{x}_{vt})]\} && \text{(covariate, aggregate risk)} \\ & + \{EU_h[E(c_{ht}|\mathbf{x}_{vt})] - EU_h[E(c_{ht}|\mathbf{x}_{vt}, \mathbf{x}_{hvt})]\} && \text{(idiosyncratic risk)} \\ & + \{EU_h[E(c_{ht}|\mathbf{x}_{vt}, \mathbf{x}_{hvt})] - EU_h(c_{ht})\} && \text{(unexplained risk and} \\ & && \text{measurement error)}. \end{aligned} \quad (13)$$

Equation (13) produces a measure of vulnerability expressed in utility units. Regressing each component of (13) on household characteristics gives the correlates of vulnerability.

3.4 Vulnerability as Uninsured Exposure to Risk (VER)

In the absence of effective risk management tools, shocks impose a welfare loss to the extent that they lead to a reduction in consumption. This, too, is a dimension of vulnerability that a third approach, vulnerability as uninsured exposure to risk, explores. It differs from VEP measures in that it is backward looking; it is an ex post assessment of the extent to which a negative shock caused a welfare loss rather than an ex ante assessment of future poverty. It differs from VEP and VEU measures in that there is no attempt to construct an aggregate measure of vulnerability.

Consider household h residing in village v at time t . Define $\Delta \ln c_{htv}$ as the change in log consumption or the growth rate in total consumption per capita of household h , in period t (i.e., between round t and round $t - 1$), and let $S(i)_{tv}$ denote covariate shocks, and $S(i)_{htv}$, idiosyncratic shocks. Let D_v be a set of binary variables identifying each community separately, and let X be a vector of household or household head's characteristics. Lastly, denoting $\delta, \beta, \gamma, \delta$, and λ as vectors of parameters to be estimated and $\Delta \varepsilon_{htvt}$ as a household-specific error term, we have

$$\Delta \ln c_{htv} = \sum_i \lambda_i S(i)_{tv} + \sum_i \beta_i S(i)_{htv} + \sum_{tv} \delta_v (D_v) + \delta X_{hvt} + \Delta \varepsilon_{htvt}. \quad (14)$$

The estimated values for λ and β in (14) identify the magnitude of covariate $S(i)_{tv}$ and idiosyncratic $S(i)_{h tv}$ shocks respectively net of the mitigating role played by private coping strategies and public responses. By quantifying the impact of these shocks, this approach identifies which risks would be an appropriate focus of policy. Tesliuc and Lindert (2002) take this approach. In their model, equation (15) below, the *level* of (log) consumption is determined by covariant— $S(i)_{tv}$ —and idiosyncratic— $S(i)_{h tv}$ shocks—as well as fixed household characteristics such as location, age, sex, and education of the household head.

$$\ln c_{h tv} = \alpha + \sum_i \lambda_i S(i)_{tv} + \sum_i \beta_i S(i)_{h tv} + \delta X_{h tv} + \varepsilon_{h tv} \quad (15)$$

They note that a household not affected by any shocks would have predicted consumption ($\ln c_{NS, h tv}$) of

$$\ln c_{NS, h tv} = \alpha + \delta X_{h tv} + \varepsilon_{h tv} \quad (16)$$

and so the impact of shocks is the difference between (15) and (16). (A variant of equation (14) involves replacing $\sum_i \lambda_i S(i)_{tv}$ and $\sum_i \beta_i S(i)_{h tv}$ with $\Delta(\ln y_{vt})$ —the growth rate in average community income—and $\Delta \ln y_{h tv}$ —the growth rate of household income, respectively.)¹³

Ligon and Schechter (2002) note that under this approach, vulnerability to shocks does not depend directly on the household’s level of consumption. Put another way, unlike the “vulnerability as expected poverty approach,” no welfare weights are attached to changes in consumption among different households. This weakness can be redressed. Interacting $\Delta \ln y_{h tv}$ with household characteristics allows the impact of income shocks to differ across different groups. A related approach is to stratify the sample on the basis of some pre-shock characteristic and estimate equation (15) separately for different groups (see Hoddinott and Kinsey 2001 for an example).

The literature on vulnerability as uninsured exposure to risk uses four variants of equation (14). These are

$$\Delta \ln c_{h tv} = \sum_{tv} \delta_{tv} (D_{tv}) + \sum_i \beta_i S(i)_{h tv} + \gamma X_{h tv} + \Delta \varepsilon_{h tv} \quad (17)$$

¹³ A drawback to this approach is the assumption that positive and negative income shocks have symmetric effects. The factors that determine whether one can deal with positive shocks compared to dealing with negative shocks may be quite different in general and between households (Dercon 2002). While credit may be hard to obtain, savings (via livestock or grain stores) is likely to be easier. Thus, interpreting β in (13) as a measure of vulnerability—rather than a measure of consumption insurance—could lead to wrong inferences about the vulnerability of households. This can be overcome by replacing $\Delta \ln y$ with two covariates denoting absolute values of the size of positive and negative income changes or by using splines.

$$\Delta \ln c_{htv} = \sum_{iv} \delta_{iv} (D_{iv}) + \beta \Delta \ln y_{htv} + \delta X_{hvt} + \Delta \varepsilon_{hvt}, \quad (18)$$

$$\Delta \ln c_{htv} = \alpha + \sum_i \lambda_i S(i)_{iv} + \beta \Delta \ln y_{htv} + \delta X_{hvt} + \Delta \varepsilon_{hvt}, \quad (19)$$

$$\Delta \ln c_{htv} = \alpha + \beta \Delta \ln y_{htv} + \gamma \Delta (\overline{\ln y_{vt}}) + \delta X_{hvt} + \Delta \varepsilon_{hvt}. \quad (20)$$

All specifications include controls for fixed household characteristics by including a set of covariates such as the education, ethnicity, and sex of the household head or by estimating the model using household-level fixed effects. They differ in their representation of shocks. Equation (19) focuses on the impact of idiosyncratic shocks on changes in consumption. The set of survey round/community interaction terms control for the role of aggregate (or covariate) shocks common to all households within any given community and survey round. As changes in consumption are expressed in logarithms, they also account for potential differences in the round-to-round inflation rate across communities.

Section 4.4 (below) notes several methods, and limitations, associated with the measurement identification of these shocks. Further, there is always a nagging worry that some shocks are missed. One way of addressing both concerns simultaneously is to include $\Delta \ln y_{htv}$, the growth rate of household income change, instead of these shock variables, on the grounds that the parameter β captures the impact of *all* idiosyncratic shocks on changes in consumption. This is the specification outlined in equation (18). A problematic feature of estimating equation (18) is that estimates of β are vulnerable to two sources of bias. First, as explained in Section 2, households respond to income shocks with a variety of strategies, so $\Delta \ln y_{hvt}$ can hardly be regarded as exogenous. Further, estimates of income and of changes in income are notoriously difficult in many developing country contexts, giving rise to legitimate concerns regarding measurement error. Endogeneity and measurement error concerns can be addressed via the use of instrumental variables. The idiosyncratic shock covariates described earlier are obvious instruments, but this begs the question as to why one would adopt equation (18) over equation (17).

Equations (19) and (20) provide two methods for focusing attention on consumption variability arising from covariant risk. Analogous to (17), an alternative strategy is to include representations of positive and negative covariant shocks as regressors, as is done in (19). Changes in prices, wages, and rainfall are frequently used as covariates. Dercon and Krishnan's (2003) study of the effect of public transfers such as food aid on risk sharing in Ethiopia allows for different effects of "better than normal" and "worse than normal" rainfall. Equation (20) allows the growth rate in household

consumption to be determined by the growth rate in household income as well as the growth rate in average community income denoted by $\Delta(\overline{\ln y_{vt}})$. Evidence that the growth rate in average community income has a significant role in the growth rate of household consumption (i.e., $\gamma \neq 0$) is consistent with the hypothesis that some risk sharing is taking place within communities. As in the discussion of income growth at the household level, it may be instructive to separate $\Delta(\overline{\ln y_{vt}})$ into positive and negative changes.

The data requirements associated with the estimation of (17) and especially (18), (19), and (20), are severe. Not only is it necessary to have a panel household survey but for the latter three specifications, the survey must collect information on both household consumption and income. If the coefficient β summarizing the partial covariance between consumption and income changes is to be estimated with some precision at the household level instead of just for the sample as a whole, it is necessary to have at least three or four repeated observations per household in the panel.

4. DATA SOURCES AND ISSUES

In this section we briefly review data sources on risk and vulnerability, highlight issues of measurement and interpretation, and make suggestions to improve data sources for risk and vulnerability measurement.

4.1 Issues for Data Collection

Covariate and Idiosyncratic Shocks

Although econometric approaches do not require any a priori classification of shocks according to their degree of covariance, classifying risk and shocks according to idiosyncratic or spatially covariate can help identify data sources. For spatially covariate risks and shocks, community information and secondary sources such as rainfall and administrative data on wages and prices are a valuable complement to household data. By contrast, information on risk management instruments and outcomes is more likely to be available at the household level, although some risk-management institutions may operate at the community level, such as public works programs. One problem with matching household data with secondary data is the difficulty of mapping and matching localities—often one loses households from surveys because they do not match the spatially referenced data. Administrative boundaries may also be misleading when matching rainfall data, where topography plays a more important role. Prior knowledge regarding the degree of covariance of shocks may help inform data designers regarding the level of aggregation: if shocks are highly covariate, it may be more cost-effective to collect data at a higher level of aggregation.

In practice, however, even within well-defined rural communities, variance decomposition analysis reveals that few risks are purely idiosyncratic or common.

Variance decomposition analysis involves computing the contribution of village-level variance to total variance: the lower its contribution, the more idiosyncratic the shock. Dercon (2002), drawing from his work in rural Ethiopia (Dercon and Krishnan 2000), finds that most shocks have both idiosyncratic and common parts. A priori classifications may also misclassify shocks. In a study on Guatemala, while shocks were classified a priori into idiosyncratic or covariate, a variance decomposition test showed that location alone explained less than 25 percent of all shocks that were classified as covariate (except inflation). The shocks with a high degree of covariance at the local level were bad harvests and income losses, which were classified a priori as idiosyncratic (Tesliuc and Lindert 2002). Respondent reports of the impact of shocks may also have systematic biases. In the same study on Guatemala, respondents tended to “complain” about covariate shocks and to be more “honest” about the impact of idiosyncratic shocks, but the share of covariate shocks that had no negative impact on household income or wealth was significantly larger than the equivalent share of idiosyncratic shocks.

Risk Responses

Information on risk responses is also difficult to obtain. First, obtaining information on expectations is inherently difficult. A person’s answer regarding questions regarding “expected yield” or whether it was a “normal” year involves three elements: the person’s understanding of the objective distribution of risks, the person’s own response, and the person’s own risk preferences. Without conducting experiments to elicit a person’s risk distribution, survey designers resort to historical markers as well as well-defined, specific recent events to get at a person’s actual and potential responses to risk. In Bangladesh, for example, floods occur yearly, but the 1998 floods were memorable because of their severity. By asking about well-defined, specific recent events, one can get some idea about the risk distribution that the person faces. Discrete events can also be recalled over a longer period than recurring events. Second, depending on the timing of the survey (see below), a response could be identified either as an *ex ante* or an *ex post* response. Take as an example membership in a rotating savings association (ROSCA). Suppose that the member was interviewed prior to a shock that enabled her to withdraw funds from the ROSCA. In that case, membership in the ROSCA would be interpreted as an *ex ante* risk management mechanism. However, suppose she was interviewed after a shock, and she had just withdrawn funds from the ROSCA. Without knowing the date that she joined the ROSCA in reference to the timing of the shock, it would be difficult to establish whether a particular mechanism was used *ex ante* or *ex post*.

Timing and Frequency of Surveys

The timing of the survey work is important. As Figures 2 through 6 show, shocks work with time lags, and have different distributions. Because shocks are, by definition, unanticipated, it is often pure coincidence that a survey will be able to capture information on shocks (particularly if it is a one-time shock) unless the survey was conducted for that purpose. A case can certainly be made for shorter surveys that are fielded more frequently for monitoring purposes, rather than long surveys that are fielded at longer intervals. If, however, it is only feasible to field a survey after a long interval has elapsed, the risk and shocks module should be designed to elicit dates (even if approximate) when certain shocks occurred. This would enable analysts to distinguish between more recent shocks and those in the distant past, and examine whether the impact of shocks persists over the longer term. Examples of these are the shocks modules implemented in the Philippines and Bangladesh, which have 18-year and 10-year recall periods, respectively (Quisumbing, McNiven, and Godquin 2007; Quisumbing 2007).

Cross-Validation of Responses

Cross-validation is important if different data sources are inconsistent. For example, there may be disagreement between household-level data and cluster-level data. Depending on whether geographic boundaries are drawn and where the household is actually located, administrative data may not be relevant to households in a particular cluster, if households obtain public services from a municipality other than their official place of residence. Cross-validation within the household may also be necessary. Often, we rely on the head of the household to report on assets or risk responses of other household members. Evidence from Indonesia (Frankenberg and Thomas 2001) suggests that husbands tend to underestimate their wives' asset holdings and vice versa.

4.2 Types of Data and Methods of Data Collection¹⁴

Because we are interested in household responses to risk and household vulnerability, we emphasize data from household surveys, supplemented by data from secondary sources. It is useful to distinguish types of data from methods of data collection. Data can be classified into quantitative or qualitative; methods into noncontextual and contextual. In a survey-based context, quantitative data measure the degree to which a feature is present, while qualitative data are numeric observations that denote the presence or absence of a characteristic or membership to a particular category. Qualitative data can be analyzed using quantitative methods, e.g., they can be used to

¹⁴ For a more comprehensive discussion of types of data and methods of data collection, see Booth et al. (1998), Hentschel (1999), and Moser (2001). For more detail on data sources, issues, and innovations, see Hoddinott and Quisumbing (2003b).

calculate percentages, frequencies, chi-squares, or other statistics (Chung 2000). Qualitative data are also defined in terms of textual or visual data that have been derived from interviews, observations, documents, or records. While these data are often associated with methods that require “intensive, often repeated encounters with small numbers of people in their natural environment” (Chung 2000, 337), a distinction between survey-based and contextual methods (Hentschel 1999; Moser 2001) is more useful. Contextual methods are those that attempt to understand human behavior within the social, cultural, economic, and political environment of a locality (Hentschel 1999). Survey-based methods, on the other hand, involve structured interviews of a representative household sample to obtain information on a range of questions, and preformulated, closed-ended, and codifiable questions are usually asked to one household member (often the head) during one or two visits.

Survey-Based Methods

Single-Cross Section of Households. A cross-section survey of households, conducted at a single point in time, is often the only data source for conducting risk and vulnerability assessments. While adequate for a poverty assessment, a single-cross section is problematic for measuring vulnerability because of the absence of data from more than one point in time—that is, this data set does not have any intertemporal variability. Consequently, users of single cross-sections have used cross-sectional variability as a proxy for intertemporal variability. However, identifying the household characteristics that are associated with vulnerability requires making strong assumptions about the stochastic process generating consumption, in particular assuming that the cross-sectional variance can be used to estimate intertemporal variance. While the cross-sectional variance can explain that portion of intertemporal variance due to idiosyncratic components or cluster-specific shocks, it will not capture intertemporal or aggregate (household invariant by time-varying) shocks. It may produce good estimates of vulnerability if the distribution of risks and risk management instruments is similar over time (Tesliuc and Lindert 2002), if the macroeconomic environment is stable and if shocks do not generate survivorship bias. They are less well suited to capturing the impact of large aggregate shocks (Hoddinott and Quisumbing 2003b).

Single cross-sections can still be used for vulnerability assessments if they are supplemented with other data sources, such as historical or time-series data on cropping patterns and weather events. They can also be supplemented by qualitative, contextual studies. If the analyst knows beforehand that risk and vulnerability measurement is one of the objectives of conducting the household survey, retrospective questions can be included to capture, albeit imperfectly, information about past shocks as well as *ex ante* coping mechanisms.

Repeated Cross-Sections. A number of countries undertake household surveys at regular intervals, but that are not panel surveys because they do not return to the same households. Examples of these are the Family Income and Expenditure Surveys in the Philippines, the Welfare Monitoring Surveys in Ethiopia and Kenya, and the SUSENAS surveys in Indonesia. If the repeated cross-sections are drawn from the same sampling frame, then cluster panels can be created, permitting an analysis of intertemporal variation within the cluster, even if the households covered within each cluster may be different.

Unlike a single cross-section, repeated cross-sections can capture intertemporal variation. Unlike panel data, which are relatively rare, repeated cross-sections are more readily available, being part of many countries' regular statistical activities. Construction of cluster or community averages also is a way of creating observations on a whole range of variables over time, when panel data are not available. If the sample sizes are large enough, repeated cross-sections can be used to create pseudo-panels of cohorts.

How useful are cluster data for making inferences about household vulnerability?¹⁵ The basic assumption underlying this approach is that each cluster represents a “representative household,” which may not be the case if households varied widely in their characteristics and behavior across clusters, and if clusters were given equal weights in the regression analysis. However, even if each cluster did not consist of the same number of households, or if clusters were of different size, this concern can be addressed in the regression analysis using sampling weights. A second concern, raised in the context of cross-country studies (Behrman and Deolalikar 1988) is that the use of average data may be misleading if the distributional issues are important and if the distribution is different across clusters. Even though households within clusters tend to be more homogeneous than households within countries—and thus distributional differences are of less concern—it may be advisable to do a variance decomposition for some measures of interest to see whether intra-cluster variability is greater than inter-cluster variability. So long as the distribution of “representative households” reflects the distribution of household and locality characteristics, the estimated coefficients of the *ex ante* mean and variance of future consumption will provide a good indication of the relative importance of the determinants of household vulnerability.

*Panel Data.*¹⁶ The vulnerability measures discussed in this chapter are best estimated using panel data. Although a series of repeated cross-sections could lend itself to synthetic cohort analysis, panel data have a number of advantages for undertaking risk and vulnerability assessments: (1) in the absence of measurement error, panel data enable more precise estimation of changes in variable means; (2) they are suited to

¹⁵ This discussion draws heavily from Christiaensen and Subbarao (2001).

¹⁶ This discussion draws heavily from Glewwe and Jacoby (2000).

estimating changes at the individual level whereas repeated cross-sectional surveys only permit comparisons over time across broad groups; (3) they provide more accurate data on past events than retrospective surveys; and (4) they may be cheaper to collect than repeated cross-sections, since a subset of basic information will not need to be collected, but rather updated. An especially attractive feature of panel data is its suitability to fixed-effects analysis, which allows the researcher to control for unobservable time-invariant characteristics of households and communities.

Panel data, however, need to be used sensibly: information on time-varying characteristics also needs to be collected; attention needs to be paid to nonrandom attrition, which may lead to bias if households or individuals that remain in the sample differ in unobserved ways from those that have left; and one must distinguish between transitory shocks and measurement error in the data, which is especially important when making inferences about transitory and chronic poverty. Other problems with fixed-effects estimation have to do with the loss of statistical degrees of freedom, the loss of the ability to estimate coefficients on time-invariant variables (which will drop out in the fixed-effects estimation), and the possibility that differencing will worsen the problem of measurement error.

From a survey logistics perspective, collecting panel data will need to deal with respondent fatigue, which could be a factor leading to attrition due to non-response or unwillingness to be surveyed. Panel data based on a sampling frame of dwellings may miss groups like pastoralists. Panel data based on a household sampling frame will have to face issues like drastic changes in household structure due to death or migration, or simply aging. Also, panel data can be expensive. Last, over time, the panel will no longer be representative of the population, unless households are added to maintain the representativeness of the panel.

*Locality Data and Contextual Methods*¹⁷

Locality data collected from community questionnaires and secondary sources provide important information on the household's environment and can be used to supplement information from household surveys. Locality information can be obtained from a variety of sources: "community questionnaires" on local infrastructure, health, and education facilities; administrative sources; market price surveys; archives; rainfall stations; focus groups and key informants detailing local histories; and, where appropriate, other primary data sources such as Demographic and Health Surveys. Data from contextual methods also provide insights into the social and cultural environment of households, and may be extremely useful in examining individual perceptions of risk and vulnerability and sensitive issues that are less suitable for survey-based methods. Where the analyst has no other household-level data source but a cross-sectional survey, locality

¹⁷ See Hoddinott and Quisumbing (2003b) for more detail.

data may be the only source of information on intertemporal variation. Contextual methods can get at people's perceptions of risk and vulnerability, and explore issues that may be less amenable to survey questionnaires, including sensitive issues such as intrahousehold relations, crime, illness, magic, and politics, as well as more "complicated," multidimensional issues such as power relationships, trust, and belief systems. Contextual methods can also be especially useful in drawing up a timeline of shocks and major events affecting the community.

4.3 Analytical Issues

Most household data on positive and negative shocks are obtained using recall methods, typically by asking a household to list important events that have taken place, say, in the past 10 years, when this event took place, and the impact of the event on household welfare (consumption, asset holdings) or behavior. Aside from the very real possibility of recall bias, the reliance on shocks data brings out two important issues for analysts of risk and vulnerability: attribution of causality and endogeneity.

Attributing Causality

Self-reported shocks represent attributions of causality by respondents rather than the events themselves. Consider a poor, landless rural household for whom a "normal" life is one where temporary employment has always been interspersed with periods of unemployment. Such a household might not report job loss as a "shock" when job loss is a regular occurrence. But a wealthy, urban dweller who loses her formal-sector job would report a job loss shock, because it represents a change. Both individuals have experienced a job loss shock but only the wealthy person reports the shock. This problem is not unique to shocks; Gertler, Rose, and Glewwe (2000) note similar problems in the context of obtaining information on health status. A related issue pertains to the classification of shocks. Suppose a fall in coffee prices causes a coffee farmer's income to fall and, as a result, she makes several farm laborers redundant. If one were to interview both the farmer and the laborers, the former would indicate that a covariant shock (adverse change in terms of trade) had affected her while the laborers would indicate that they had been affected by an idiosyncratic shock, unemployment. Concluding that one group (coffee farmers) was affected by a covariate shock and a second group (laborers) was affected by idiosyncratic shocks would be incorrect; both groups were affected by the same event but in different ways.

Tesliuc and Lindert (2002) provide an excellent example of such problems in their comprehensive vulnerability assessment of Guatemala. They note that the single most frequently reported shock in their survey data was inflation, but this was reported in a year where inflation was low. da Corta and Venkateshwarlu (1992) provide a second instructive example; finding that identification of drought shocks varied by class, caste,

gender, and age in their village study of economic mobility in Western Chittoor District, India. Dercon and Krishnan (2000) suggest checking such self-reported shocks by comparing it with other information found in the survey. They show, for example, that households reporting a higher incidence of “nonrainfall crop shocks” had lower levels of crop production. One solution to this problem, particularly in the case of covariate shocks, would be to use the share of households in the community that experienced the shock as a proxy for severity of the shock, instead of relying on household self-reports of severity (for an example, see Carter, Little, and Mogues 2007).

The second point relates to the attribution of causality by the analyst. Consider the following example. Suppose households in a village are all male-headed and some produce a crop that is subjected to an adverse terms-of-trade shock. Adult males leave the households affected by this shock in order to search for work, leaving behind female-headed households. Subsequently, a research team visits the village and undertakes a survey that covers shocks and household characteristics. Cross-tabulating these data would show that female-headed households are more likely to report a terms of trade shock and based on these results, one might conclude that social protection interventions should be targeted to female-headed households. Such a conclusion is, of course, incorrect: female headship is an outcome of the shock, not a correlate of vulnerability. Addressing this concern requires two actions. First, analysis of risk and vulnerability should be based around some conceptual or theoretical framework that facilitates the identification of causality. Second, empirical work should take this into account both in terms of model specification and estimation.

Shocks and Endogeneity

In modeling the impact of shocks on household welfare, it is often assumed that shocks are exogenous, unanticipated events. However, the exposure of households to several types of shocks may be endogenous by nature. For example, the risk of malnutrition can be the result of food rationing during a drought (or an outcome); deforestation can be the result of a response to risk realization; individuals can engage in crime in times of stress, but also can be victims of it, making this particular category both a source of risk as well as a response to it; etc. There are several potential mechanisms for dealing with endogeneity of risks to household behavior. A useful exploratory approach is to explicitly model the probability of the household reporting a particular type of risk, as a function of individual, household, and community characteristics.

Table 5 provides an example of this approach using the data found in Dercon, Hoddinott, and Woldehanna (2005). In their longitudinal data set, there is information collected in 1999 on household characteristics. In the 2004 survey round, respondents were asked to report different shocks (climatic, economic, etc.) that caused households to reduce consumption, lose income, or lose or sell assets. Using these data, we estimate a probit where the dependent variables are the likelihood of reporting a number of different

shocks: drought, flood, crop diseases, livestock diseases, agricultural input shocks (high prices or difficulty acquiring crop inputs), agricultural output shocks (low prices, difficulty in selling crops), nonagricultural income shocks, being a victim of crime, illness, or death. Regressors are household demographic characteristics (sex of head, log age of head, log household size), human capital (dummy variable if the head has any schooling), land (four dummy variables denoting whether household landholdings are in the 2nd, 3rd, 4th, or 5th quintile within its locality), livestock (number of tropical livestock units) and networks (dummy variable indicating if household belongs to an ethnic minority, religious minority, and whether parents of the head or spouse were considered important people in the community). In addition, we control for location and date of interview. The chi-squared statistics indicating whether these sets of characteristics are jointly significant are reported in Table 5. The striking feature of these results is the absence of correlation between these household characteristics and the likelihood of reporting shocks. Household demographic characteristics affect the likelihood of reporting illness and death shocks (older and larger households are more likely to report both) and there is some correlation between aspects of households' networks and the likelihood of reporting illness shocks.

Table 5. The relationship between household characteristics and the likelihood of reporting shocks

Shock reported between 1999 and 2004	Household characteristics observed in 1999				
	Demographic	Human capital	Land	Livestock	Networks
Drought	0.82	1.78	3.51	0.17	4.66
Flood	0.58	0.78	2.83	0.01	4.89
Crop pests	1.14	0.63	4.74	0.03	3.70
Livestock diseases	2.69	0.03	6.84	0.00	6.16
Input shocks	1.10	0.17	3.57	0.67	1.28
Output shocks	1.66	0.12	6.91	0.30	0.21
Shocks to nonagricultural income	4.73	2.24	6.68	0.13	8.57*
Crime	6.06	0.02	6.90	0.05	3.65
Illness	33.74**	0.02	1.87	2.04	16.34**
Death	22.89**	1.78	0.97	0.01	1.28

Notes: Numbers in cells are Chi squared statistics. * significant at the 10 percent level; ** significant at the 5 percent level. Demographic characteristics are sex of head, log age of head, log household size. Human capital is a dummy variable if the head has any schooling. Land are four dummy variables denoting whether household landholdings are in the 2nd, 3rd, 4th, or 5th quintile within its locality. Livestock is number of tropical livestock units. Networks consist of dummy variable indicating if household belongs to an ethnic minority, religious minority, and whether parents of the head or spouse were considered important people in the community. Location and date of interview dummy variables are included but not reported.

If the reporting of shocks is correlated with household characteristics, there are two approaches that can be taken. One is to aggregate the reporting of these shocks to the locality level, so, for example, one uses as a regressor the percentage of households reporting that they have been the victims of crime rather than the self-reports of individual households. A second would be to use community reports of shocks (say crime) instead of individual reports. A limitation to this approach is that it assumes that

these shocks have the same impact on all households. This can be redressed by interacting these aggregated shock representations with selected household characteristics (landholdings; sex of head, and so on).

Timing and Long-Term Impacts of Shocks

One possible area of concern is that few available data sources take into account the fact that risks are sometimes bundled—a flood can invite outbreaks of disease—or non-independent over time—i.e., when shocks lead to nutritional deficiencies that in turn reduce the resiliency of organisms. They can also be nonstationary over time as when shocks have permanent or persistent effects. In that sense, coping mechanisms developed today to mitigate the impacts of a shock can very well constitute future markers of vulnerability. The cumulative consequences for these events and mechanisms are currently not well understood.

Careful attention to obtaining time markers in shocks recall modules can help address these difficulties. For example, it is relatively easy to pinpoint the timing of covariate shocks such as floods, based either on recall data or on rainfall data. At the same time, a comprehensive listing of shocks, with associated dates, can help the analyst figure out the extent to which shocks are correlated. Life history methods (e.g., Davis 2006 in Bangladesh) implemented among a subset of survey households can help identify key shocks or triggers for asset decumulation and eventual decline into poverty; iterative qualitative and quantitative analysis can go even further in linking important life events (shocks) to gradual or steep declines in well-being (Baulch and Davis 2007). Time markers can also be used to examine whether shocks have persistent, or long-term, impacts. This is relatively easy to do when tracing the impact of large-scale emergencies or covariate shocks, especially using prospectively collected data, but less easy when examining the impact of idiosyncratic shocks (for example, death or illness of a household member), unless dates of the event are also obtained during household interviews.

5. USING VULNERABILITY MEASUREMENT TO INFORM POLICY

The analytical approaches to modeling vulnerability and the data sources described above can be used to answer four questions of interest: (1) Who is vulnerable? (2) What are the sources of vulnerability? (3) How do households cope with risk and vulnerability? and (4) What is the gap between risks and household coping mechanisms?

5.1 Who Is Vulnerable?

A policymaker may have limited resources that she wishes to target. In an environment characterized by the absence of shocks, characteristics correlated with poverty will provide the necessary information to implement a targeted intervention. But

in an environment characterized by frequent shocks, such an approach may be unhelpful as households move in and out of poverty. In that case, it is informative to understand who is expected to be poor, which, as explained above, is one definition of vulnerability.

The simplest approach to doing so goes back to equation (4),

$$\ln c_{ht} = \beta \mathbf{X}_h + e_h.$$

Recall that \mathbf{X}_h is a vector of household characteristics (e.g., location, characteristics of head, assets, prices, shocks) and β is a vector of parameters to be estimated. As also noted above, equation (4) can be estimated for different groups (e.g., rural and urban) and \mathbf{X}_h can include interaction terms. A simple way of getting a sense of the vulnerability of certain types of households is to predict consumption levels either by varying the values of \mathbf{X}_h or by varying the values of β . So, for example, one could simulate the impact of drought by estimating (4) but replacing mean rainfall levels with those, say 25 percent, below the mean, calculating expected consumption levels for all households and comparing this against the poverty line. Alternatively, suppose that returns to certain types of assets were to collapse. For example, suppose that the market for livestock falls apart following an import ban by a neighboring country. The impact of this could be simulated by reducing the β associated with livestock.

Section 3 suggests three additional approaches:¹⁸

- (1) Define a measure of vulnerability such as that proposed by Chaudhuri (2000), Chaudhuri, Jalan, and Suryahadi (2002), or Ligon and Schechter (2002). Group households based on these definitions of vulnerability, and compare the characteristics of the vulnerable to other groups.
- (2) Using regression techniques, determine the relationship between the vulnerability measure for each household and observable household characteristics so as to identify which characteristics are correlated with higher vulnerability.
- (3) Using the “vulnerability to risk exposure” approach, estimate the variability of consumption in response to idiosyncratic shocks for subgroups of the population.

5.2 What Are the Sources of Vulnerability?

If vulnerability is defined, in a general sense, as the welfare loss due to poverty and the welfare losses due to risk (Ligon and Schechter 2002), it makes sense to identify the proximate causes of vulnerability as they relate to structural poverty and consumption volatility (Chaudhuri and Christiaensen 2002). Identifying these causes would enable

¹⁸ Hoddinott and Quisumbing (2003a) provide additional references and examples of these approaches.

policymakers to distinguish between those who would not be vulnerable in the absence of consumption vulnerability and those who are structurally poor. For the former group, interventions that reduce consumption volatility by reducing their exposure to risk or by enhancing their ex post coping capacity could be sufficient. However, for the latter, risk-reducing interventions alone may be inadequate, and must be accompanied by interventions to increase mean consumption.

As explained in Section 2, negative shocks combined with poor risk management are a principal source of vulnerability. This suggests that combining the enumeration of shocks, described in Section 2, with the analysis presented in Section 3.4—characterizing vulnerability as welfare losses arising from uninsured exposure to risk—represents one method for identifying sources of vulnerability. Dercon and Krishnan (2000) is an example. Their dependent variable is (log) household consumption per equivalent adult net of food aid and food for work. Using household fixed effects regressions—to control for all fixed household characteristics, they examine how this outcome is affected by a rich representation of idiosyncratic and covariant shocks. They find that both idiosyncratic and aggregate shocks matter. Village-level rainfall, the crop damage assessment, and livestock disease are strongly significant and of the right sign: negative (positive) shocks have negative (positive) effects on consumption.

5.3 How Do Households Cope with Risk and Vulnerability?

In order to design appropriate social protection instruments, the policymaker needs to examine the existing mechanisms that households use to cope with idiosyncratic and aggregate shocks. This requires data on responses to shocks (the dependent variable) as well as shocks. The model to be estimated takes one of two forms:

$$R_{htv} = \sum_{tv} \delta_{tv} (D_{tv}) + \sum_i \beta_i S(i)_{htv} + \gamma X_{hvt} + \varepsilon_{hvt} \quad (21)$$

or

$$\Delta R_{htv} = \sum_{tv} \delta_{tv} (D_{tv}) + \sum_i \beta_i S(i)_{htv} + \gamma X_{hvt} + \Delta \varepsilon_{hvt} \quad (21a)$$

where R_{htv} indicates whether a given risk management mechanism was used and ΔR_{htv} indicates whether there was a change in the use of a given mechanism. By interacting shocks with fixed household characteristics, one can also determine whether different types of households (male- or female-headed; more or less educated heads, etc.) are more or less likely to use a given risk management mechanism. So, for example, finding that richer households are more likely to use a food-for-work program in response to a shock would suggest that this public risk management mechanism may not be reaching its intended target group.

In choosing between these, one should note the following. Equation (21) can be estimated using a single cross-sectional data set, whereas equation (21a) requires longitudinal data. However, there may be location specific characteristics that affect the use of particular risk management mechanisms; for example, households in areas where rainfall is uncertain may, as a matter of course, engage in income diversification; estimation of equation (21) therefore runs the risk that because $S(i)_{htv}$ (observed shocks) are correlated with ε_{htv} , estimates of β_i are biased. While household-level fixed effects regressions overcome this by differencing at the household level, if risk management mechanisms do not vary over time (e.g., the representation of the risk management mechanism is whether or not a household is a net borrower and the household is observed to borrow money in *every* period), these observations will be dropped before estimation. Skoufias and Quisumbing (2005) provide a detailed discussion.

5.4 What Is the Gap between Risks and Risk Management Mechanisms?

The conceptual framework described in Section 2 illustrates two mechanisms households use to cope with risk and vulnerability. There are *ex ante* choices made by households (such as asset accumulation) and there are *ex post* responses such as the reallocation of labor or accessing public resources such as transfers. Information on the efficacy of these risk management mechanisms can be valuable for policymakers. Building on analysis that identifies sources of risk and household responses to shocks, one can construct the following cases:

Table 5: Identifying the gap between risks and social risk management (SRM) mechanisms

Responses	Welfare impacts of shocks	
	Not significant	Significant
Private <i>AND</i> Public	A: Possibly successful SRM (but think about balance between public and private responses)	B: Existing SRM mechanisms are inadequate
Private <i>BUT NO</i> Public	A: Possibly successful private SRM (think about role of public interventions)	B: Private SRM mechanisms inadequate; consider role of public
<i>NO</i> Private <i>BUT</i> public	A: Possibly successful public SRM (think about role of private responses)	B: Public SRM mechanisms inadequate; but why no private response
<i>NO</i> Private, <i>NO</i> public	D: Shocks are unimportant	C: Existing SRM mechanisms are nonexistent

The gaps identified in Table 5 divide into four broad types. Cases where there are private and public responses to shocks and these shocks do not have significant impacts on household welfare (**A**) are cases where existing risk management mechanisms would appear to be adequate, although this should be treated cautiously. First, these responses may come at the cost of longer-term poverty reduction. Households for example, may

avoid taking risky but profitable opportunities or practice income smoothing as a substitute for consumption smoothing. Others may be able to smooth their consumption through coping strategies that deplete their assets, such as selling their livestock (Rosenzweig and Wolpin 1993), withdrawing their children from school when there are shortfalls in income (Jacoby and Skoufias 1997), or using assets as a buffer for consumption (Deaton 1992). As a consequence of all these risk management and risk-coping strategies, households may appear to be more insured, when in fact their vulnerability to future poverty may be increasing. Second, there still remains the question of the appropriate balance between private and public responses, especially when one broad category of risk management mechanism is absent.

Cases where there is a private and/or public response but the shock still has an impact on welfare (**B**) suggest that there is a need to *both* strengthen risk management mechanisms *and* consider the appropriate balance between private and public responses. Cases where shocks led to welfare losses and where there were no private or public responses (**C**) are especially serious as they are indicative of a complete absence of risk management mechanisms. By contrast, cases where shocks do not have significant impacts and where there are no responses to such shocks are suggestive of shocks that are likely to be unimportant from a policy perspective (**D**). As in discussions earlier, these tables can be further disaggregated by characteristics of the household as a way of determining how effectively public responses are targeted.

A second approach is to stratify the sample on the basis of pre-shock characteristics that are assumed to represent *ex ante* risk management mechanisms. Hoddinott and Kinsey (2001) provide an example. Working in Zimbabwe, they draw on qualitative fieldwork that showed that households accumulated livestock in the expectation that these assets would be sold or consumed in the event of a drought. Their data span a number of years that includes a major drought. They estimate a variant of equation (10), the variant being that the dependent variable is growth in the heights of children 12-24 months (rather than growth in consumption) for two groups: children residing in households below and above the median value of pre-drought livestock holdings. They find that drought only affects the growth of children residing in poorer households, suggesting that the *ex ante* risk management mechanism is effective for mitigating the impact of drought shocks on this welfare indicator. They also show that investments in women's education provide a substitute in the absence of asset accumulation, with maternal schooling increasing child growth but only in poorer households.

6. CONCLUSIONS

This chapter provides an overview of quantitative tools for the assessment of risk and vulnerability assessments using micro data. It focuses on three broad classes of

techniques, vulnerability as expected poverty, vulnerability as expected low utility, and vulnerability as uninsured exposure to risk. These approaches are described more fully in Section 3; Section 4 provides a complementary discussion of the data needs associated with these. Together with the material presented in Section 5, this “toolkit” provides quantitative techniques that can address five components of risk and vulnerability assessments:

- What is the extent of vulnerability? (*Section 3*),
- Who is vulnerable? (*Section 5.1*),
- What are the sources of vulnerability? (*Section 5.2*),
- How do households respond to shocks (*Section 5.3*), and
- What gap exists between risks and risk management Mechanisms (*Section 5.4*)?

In principle, an ideal vulnerability assessment would incorporate all five components. In practice, vulnerability assessments will reflect specific objectives of the practitioner and the resources—time, money, and data—available for this work. Given constraints, what should assessments do?

There is a strong case for *always* undertaking three analyses:

- Identifying the correlates of vulnerability. Differentiating these groups using observed household characteristics, including location, may help policymakers improve program targeting. For example, programs which help households cope with unexpected shocks are better targeted to areas of high vulnerability but low poverty, while programs targeted to structural poverty are better placed in areas with high poverty ranking but low vulnerability ranking.
- Examining the sources of vulnerability by characterizing risks and shocks faced by the population as well as the distribution of those shocks. It is not possible to formulate appropriate risk management strategies in the absence of information about the nature of shocks. If suitable household survey data are not available, qualitative data, data from secondary sources (data on macroeconomic indicators, rainfall data, administrative data, demographic and health data, agricultural census data) will be valuable.
- Determining the gaps between risks and risk management mechanisms. By examining the impact of shocks and household responses to them—as explained in sections 5.3 and 5.4—this analysis assists the practitioner in determining whether the appropriate response is to develop interventions that enhance existing private risk management mechanisms or to design better public risk management mechanisms. Note that this can be undertaken for a variety of welfare measures including consumption, health, and education.

By contrast, constructing a summary measure of vulnerability should be considered on a case-by-case basis. As discussed in section 3, this is desirable where measured poverty is low but a substantial proportion of households have consumption just above the poverty line so that an adverse shock could tip many households into poverty. However, as also explained in section 3, these summary measures either rely on assumptions or are particularly data-intensive.

Fortunately, data sources that can be used for undertaking risk and vulnerability assessments are increasing, even if their coverage is not uniform nor always of high quality. More household surveys are being designed and implemented so that a panel can be built up over time, and with the collection of geo-referenced data at the household level, household surveys can be better linked to administrative or meteorological data. Nevertheless, in designing surveys and, in particular, retrospective shocks modules, analysis will need to pay careful attention to timing of recall of adverse events, so that causality and bundling of shocks can be taken into account. Methods to control for the possible endogeneity of shocks reporting may also need to be employed. Finally, depending on the reasons for undertaking a vulnerability assessment, the analyst may wish to supplement quantitative household data with administrative data that have better geographic or time-series coverage, or with qualitative assessments that are better able to capture people's perceptions of the causes and consequences of vulnerability.

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