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Methods for Microeconometric Risk and Vulnerability Assessments

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1. INTRODUCTION

Interventions designed to address vulnerability are becoming increasingly prominent. But their design and implementation are hampered by the relative novelty of the 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. With conceptual and analytical work still at the "let a hundred flowers bloom" stage, one might be forgiven for thinking that vulnerability as a focal point is too new for 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 as compared to some benchmark in a world where 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 vulnerability assessments typically express welfare in terms of consumption, and the norm or benchmark as the poverty line, vulnerability is a sufficiently general concept so as to encompass many dimensions of well-being. One could think of vulnerability in terms of the likelihood that a new-born will grow more slowly than anthropometric norms, the likelihood that an 18 year old woman will die during childbirth in the approximately 20 years she will be of child-bearing years, the likelihood that a seven year will complete primary school. Vulnerability can be assessed at the individual or household level; it can also be aggregated over these units of observation.

This "toolkit" provides quantitative tools to practitioners who want to undertake risk and vulnerability assessments using household data. 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 econometric 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?[1] Section 6 concludes by presenting guidelines for practitioners undertaking risk and vulnerability assessments.

2. RISK, RESOURCES AND VULNERABILITY: A CONCEPTUAL FRAMEWORK

Our first step is to link the sources of risk that households face, the resources (public and private) and the risk management techniques available to them, and vulnerability—or the "risk chain."[2] Three components comprise the core of this conceptual framework: 'settings', 'assets' and 'activities'. *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 newly formed 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 and 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

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[1] A recurrent subtext of these discussions is the importance of data on shocks, risk management mechanisms and outcomes. A companion paper (Hoddinott and Quisumbing, 2003) describes techniques and sources of such data.

[2] 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).

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

general 'rules of the game' in which exchange takes place which, in turn, is a partly a function of the political setting which 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. Note that these settings will vary between the local, regional, national and global levels. Settings include covariate or common sources of risk (e.g., floods, pollution, social or political unrest), ex ante risk management instruments (actions that reduce risk, reduce exposure to risk or mitigate its adverse impacts; e.g., infrastructure construction enables markets to function more efficiently, reducing the adverse impact of drought on consumption) and ex post responses to shocks (e.g., the provision of public works).

Within these settings, the household has endowments of capital and labor. In this context, capital is broadly defined to include 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.

Figure 1 shows that this household allocates these endowments across a number of activities. For this rural household, these have been divided into food crops, cash crops and other income generating activities. Again, these distinctions should not be read too literally; they could be easily aggregated further into say agricultural and nonagricultural activities, or disaggregated further by crop and livestock type. Note that these allocations are based on the household's perception of the level and variability of the activities' returns, as well as their covariance. For example, the household may decide to grow a mix of crops that embody differing levels of susceptibility to climatic shocks and returns. Crops may be grown in different locations, may be temporally diverse (that is, different crops may grow to maturity at different speeds) or may be intercropped.[4] Similarly, the

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[4] Note that perceptions will affect the timing of these activities as well as their intensity. Morduch (1995) provides several examples of households that delay planting until they have better information about weather conditions.

Figure 1: Conceptual Framework: Settings, assets, and activities

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┌─────────────────────────────────────────────────────────────────┐   ┌──────────┐
│  ┌───────────────────────────────────────────────────────────┐  │   │          │
│  │                          ASSETS                            │  │   │          │
│  │   ┌─────────────────────┐      ┌─────────────────────┐     │  │   │          │
│  │   │      Capital        │      │                     │     │  │   │ Settings │
│  │   │ (physical, natural, │      │        Labor        │     │  │   │          │
│  │   │  human, financial,  │      │                     │     │  │   │          │
│  │   │       social)       │      │                     │     │  │   │          │
│  │   └─────────────────────┘      └─────────────────────┘     │  │   │ Physical │
│  └───────────────────────────────────────────────────────────┘  │   │          │
│                                                                  │   │          │
│  ┌───────────────────────────────────────────────────────────┐  │   │  Social  │
│  │                        ACTIVITIES                          │  │   │          │
│  │  ┌────────────┐   ┌────────────┐   ┌────────────────┐      │  │   │          │
│  │  │    Food    │   │ Cash crop  │   │ Other income-  │      │  │   │  Legal   │
│  │  │ production │   │ production │   │  generating    │      │  │   │          │
│  │  │            │   │            │   │  activities    │      │  │   │          │
│  │  └────────────┘   └────────────┘   └────────────────┘      │  │   │ Political │
│  └───────────────────────────────────────────────────────────┘  │   │          │
│                      ┌────────────┐                              │   │          │
│                      │   Shocks   │                              │   │ Economic │
│                      └────────────┘                              │   │          │
│                      ┌────────────┐                              │   └──────────┘
│                      │   Income   │                              │
│                      └────────────┘                              │
│                      ┌────────────┐                              │
│                      │ Responses  │                              │
│                      │ to shocks  │                              │
│                      └────────────┘                              │
│                      ┌────────────┐                              │
│                      │   Prices   │                              │
│                      └────────────┘                              │
│                      ┌────────────┐                              │
│                      │Consumption │                              │
│                      └────────────┘                              │
│  ┌──────────────────────┐      ┌──────────────────────┐         │
│  │  Savings/dissavings  │      │ Consumption of goods │         │
│  └──────────────────────┘      └──────────────────────┘         │
└─────────────────────────────────────────────────────────────────┘
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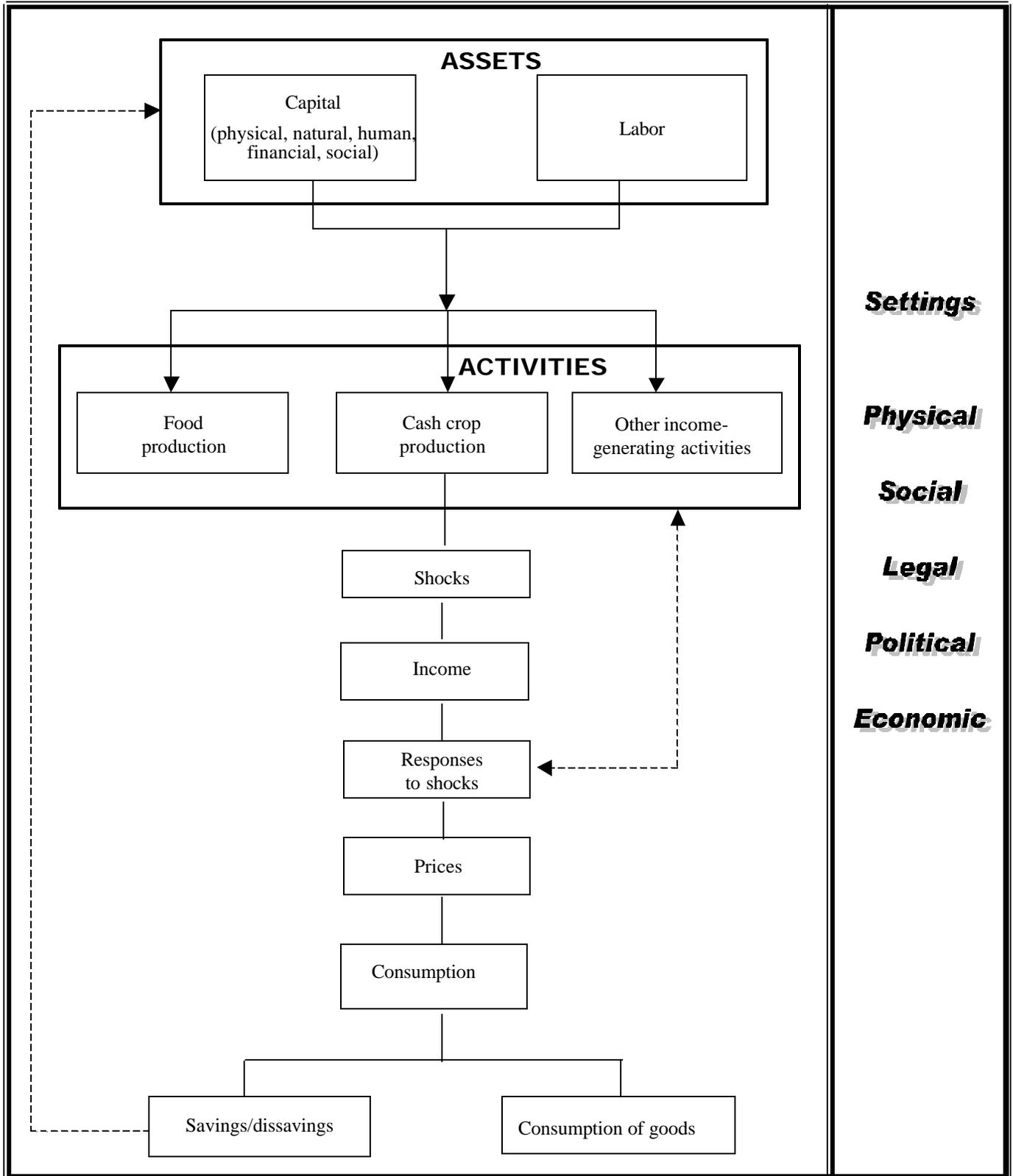
household might diversify into off-farm activities (such as handicrafts or processing) or casual wage labor.[5] The existence of interlinked transactions, such as sharecropping where access to land, labor and possibly capital and marketing are tied together, is another example of how the presence of shocks causes households to adopt strategies that protect consumption at the cost of lowered incomes (Bell 1988). The liquidity of these assets may also affect entry into activities. For example, Dercon (1996) and Dercon and Krishnan (1996) find that in Ethiopia and Tanzania, the possession of more liquid assets such as livestock is a precondition for entry into higher return, but higher risk, activities.

The relationship between endowments, activity choice and income is affected by the likelihood that of a shock occurring, what Heitzmann, Canagarajah and Siegel (2002) refer to as "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. These realizations affect both the stock of endowments and/or the returns to these endowments. Idiosyncratic shocks tend to reflect the influence of diverse, difficult to predict factors. The lengthy illness of an economically active adult is typically given as an example of an idiosyncratic shock that affects the stock of endowments. A disease that affects the quality of the tobacco crop of a smallholder is an example of an idiosyncratic shock that reduces returns to that particular activity. As already noted, large-scale disasters, such as droughts, earthquakes, floods or landslides are examples of covariant shocks that destroy physical assets. Sen (1981) notes that in the aftermath of droughts, there is often a dramatic fall in demand for individuals providing services, such as barbers and tailors. Such individuals therefore experience a covariant shock that reduces returns to their activities. Table 1 in Hoddinott and Quisumbing (2003)—the companion paper to this document that provides a discussion of data sources for vulnerability analysis—provides a detailed taxonomy of these risks.

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[5] Alderman and Paxson (1992), 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.[6] 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, as shown by Kochar (1999) for south India. 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. For example, Jacoby and Skoufias (1997) note that adverse income shocks may cause households to reduce the schooling of girls in semi-arid India. They may attempt to gain access to resources from the state, such as cash transfers or employment on public works programmes. Alternatively, they may draw on private sources, such as remittances or gifts, or attempt to access credit markets.

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.

Before continuing, note four caveats. 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. 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. 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

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[6] It is worth noting that households may decide to allocate some 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.

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households lobby governments for resources). 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. Rather than assume that the household has an endowment of assets, assume that assets are held individually. Allocations of assets to activities is a function of intrahousehold allocation rules, themselves a function of the settings in which the household is placed. So, for example, changes in the legal environment—such as laws banning wage discrimination against women—will change the allocation of assets to activities within the household. Some shocks may be individual specific. Further, changes in these settings will influence household consumption decisions. For example, strengthening women's rights to assets upon household dissolution will enhance women's bargaining position within the household.[7]

Lastly, this framework implicitly expresses poverty in terms of consumption of goods or commodities. Sen (1988) argues, such a view of well-being is too narrow, that the focus of development analysis should be broadened to include the nature of the life that people succeed in living. These concerns can be incorporated into our conceptual framework through extensions that take us from the determinants of the consumption of goods to the achievement of a broader set of development objectives. Consistent with interest in attaining the Millennium Development Goals, Heitzmann, Canagarajah, and Siegel (2002) include infant, child and maternal mortality rates, child malnutrition, and indicators of schooling (enrollment, attainment of four years of schooling, ratio of girls/boys in primary and secondary school) in their list of outcome indicators.

Mindful of these caveats, consider the next agricultural cycle. The household's stock of physical, financial and social capital will have been altered by its responses to the income shocks described above. With the experience gained from the previous year, the household's expectations of the returns and variability to different activities will also have been revised. It will also have accumulated human capital in the form of 'learning by doing'. Additionally, the household may have acquired new information on how

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[7] See McElroy (1990), Haddad, Hoddinott, and Alderman (1997), and Quisumbing and Maluccio (2003).

effectively it can cope with adverse shocks. The process described above is repeated continuously over the life cycle of the household: endowments are allocated to different activities, they experience shocks and may engage in various income and consumption smoothing behaviors. This leads to further changes in stocks of capital and a further updating of expectations.[8]

Practitioners undertaking risk and vulnerability assessments can exploit a conceptual framework in their work by noting that a) shocks affect assets, activities and outcomes and b) covariate shocks are expressed in terms of changes in settings. Table 1 enumerates these in greater detail,[9] and the methods for obtaining information on shocks

Table 1: A taxonomy of shocks

Shocks affecting:	Specific examples:
Assets	- Natural disasters such as heavy rainfall, flooding, landslides, volcanic eruptions, earthquakes, hurricanes, strong winds as well as epidemics - Social disruption such as crime, violence, terrorism, gangs, ethnic strife, civil war, breakdowns in traditional commitments of trust and reciprocity - Changes in legal environment eroding or eliminating tenure security or title to property - Political shocks such as riots or coup d'état resulting in property losses, temporary/permanent confiscation of physical assets or labor (through abduction, conscription or imprisonment), forced relocation - Health shocks such as epidemics, illness, injury, accidents and disability - Economic shocks such as unemployment, loss of value of financial assets resulting from inflation, stock market or exchange rate collapses, changes in fundamental structure of the economy (eg. transition from centrally planned to mixed or market economy)
Activities	- Disruptions in access to inputs resulting from the natural disasters, social, legal and political shocks described above - Reductions in output resulting from the natural disasters, social, legal and political shocks described above - Output price risk resulting from the natural disasters, social, legal and political shocks described above as well as uncertainties in the economic policy environment such as those brought about by uncertain commitment to policies, exchange rate shocks, changes in pricing policy and exogenous changes in product demand - Covariant movements in asset values and returns to activities - Inability to enforce formal or informal contracts for both inputs and output
Outcomes	- Price risk in consumption markets, esp. for food - Food availability and rationing - Uncertainties in access to publicly provided goods such as schools and health facilities

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[8] Although this framework is presented descriptively, placing its key components in a more formal theoretical model is relatively straightforward, see Deaton (1992) and Dercon and Krishnan (2000b).

[9] As do Heitzmann, Canagarajah and Siegel (2002).

is outlined in our companion paper, Hoddinott and Quisumbing (2003). In the context of a risk and vulnerability assessment, a useful output in its own right is an enumeration of these shocks and cross-tabulation of these by region, activities, socioeconomic status and gender.

3. QUANTITATIVE CONCEPTS OF VULNERABILITY

Our conceptual framework incorporates sources of risk, resources (public and private) available to households and risk management techniques. The interplay between these components was reflected in outcomes such as consumption and human capital accumulation. 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, such as cases where income shocks leads to reductions in girls' schooling. Our next step is to make these links more formal. We do so in three stages. In this section, we provide an introduction to quantitative concepts of vulnerability. In the following section, we review the econometric issues associated with implementing these concepts. In Section 5, we extend this discussion to the identification of the vulnerable, the sources of vulnerability, and private and public responses to shocks that threaten households with poverty.

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 assessments typically express welfare 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. One could think of vulnerability in terms of the likelihood that a new-born will grow more slowly than anthropometric norms (here, the level of welfare could be height given age and the norm being whether the child is above or below the cut-off for being considered stunted), the likelihood that an 18 year old woman will die during childbirth in the approximately 20 years she will be of

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child-bearing years, the likelihood that a seven year will complete primary school. 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 (which is also multidimensional) are linked but are not identical. For example, 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 (defined simply by whether or not the household's observed level of consumption expenditure is above or below a preselected poverty line) 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 2 and 3. The horizontal axis in Figure 2 represents predicted or expected levels of consumption at some point in the future, t+1 [10]; 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 2, 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 is shown by the horizontal rule that passes through these rectangles; they can be thought of as confidence intervals. There is no reason, a priori, to believe that such a distribution is 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

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[10] Note that Friedman and Levinsohn (2002) provide one method that, in essence, estimates the length of these horizontal rules. Specifically, they explore how changes in commodity prices are linked to changes in household welfare, as expressed in terms of the compensating variation needed to return households to their initial level of well-being.

Figure 2: Expected levels of consumption, t+1

Z, Poverty line

Expected level of consumption, t+ 1
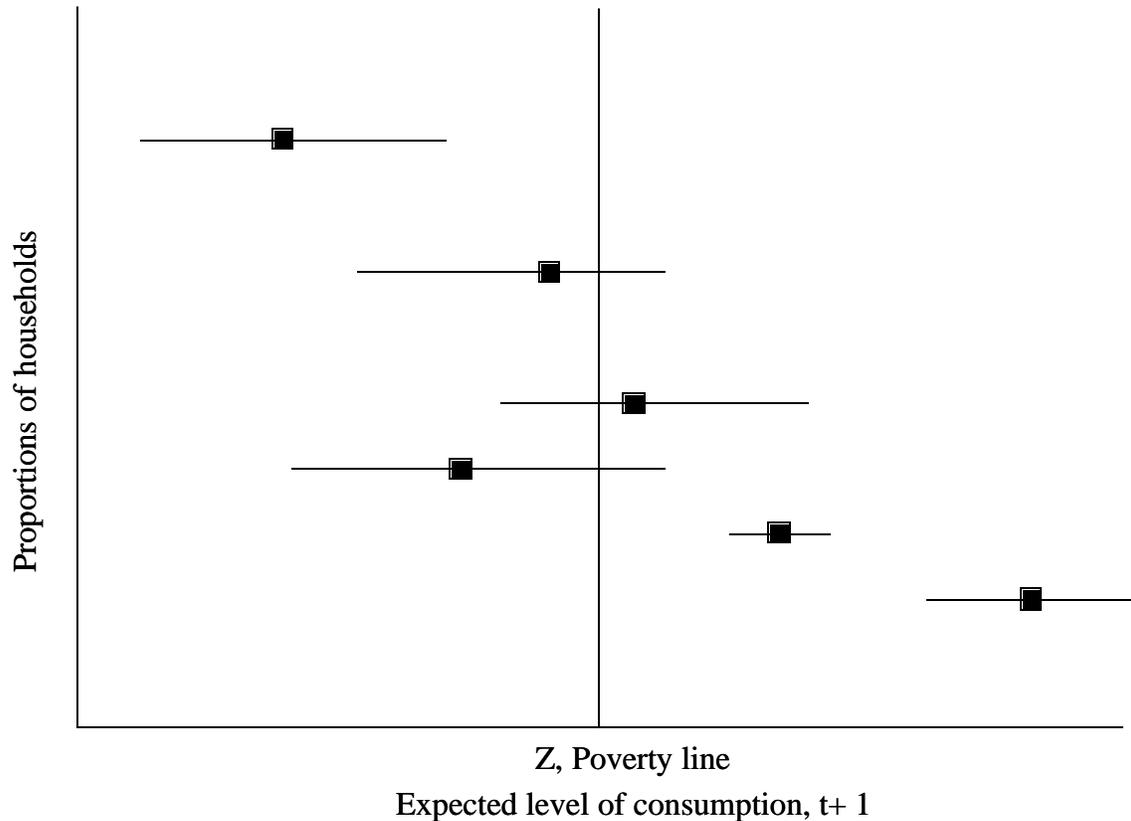
manage these shocks; such groups are characterized by having longer horizontal rules. Lastly, Figure 2 includes a vertical line denoting the level at which expected consumption exceeds the poverty line. Thus, Figure 2 conveys four pieces of information: expectations about consumption (the filled rectangles); 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 3. The proportion of households lying to the left of the vertical rule is the familiar headcount measure of poverty.

Figure 3: Realized distribution of consumption, t+1

Z, Poverty line
Level of consumption, t+ 1
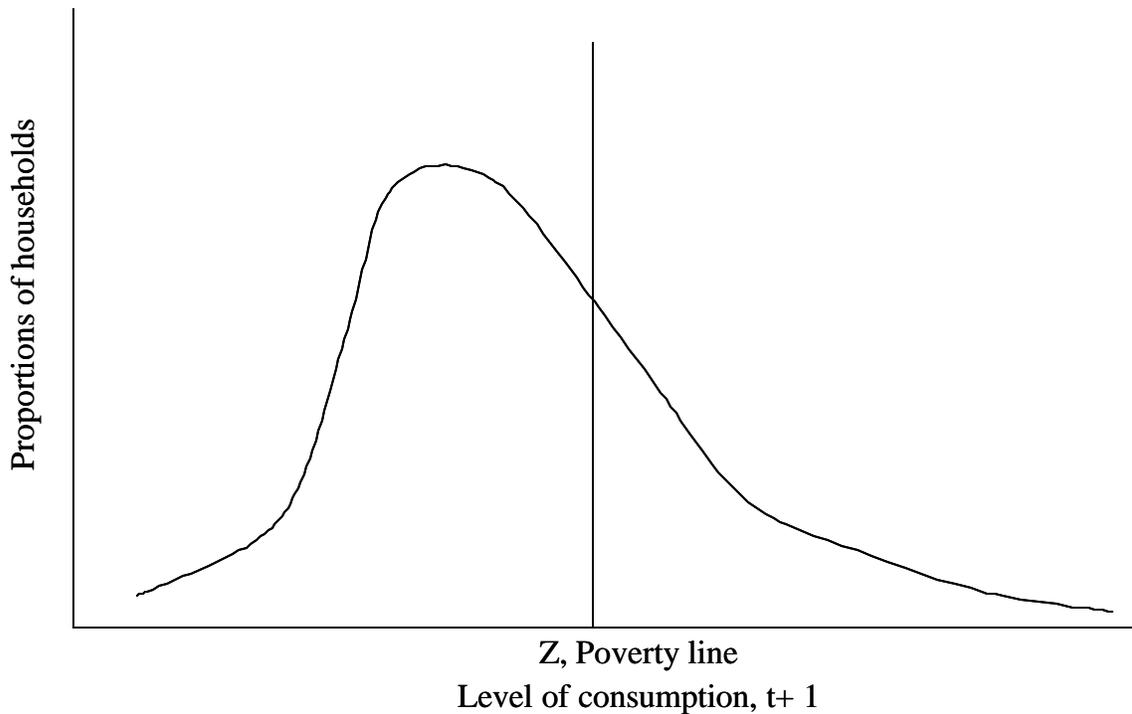
There are three principal approaches to assessing vulnerability: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER).[11] All share a common characteristic, namely they construct a model that predicts a measure of welfare. In the examples here, this is consumption, but as noted above, other welfare indicators could be used instead. VEP and VEU measures 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 2— lies to the left of the vertical rule. VEP and VEU approaches measure vulnerability at the

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[11] Our thanks to Stefan Dercon and Ethan Ligon for a series of suggestions regarding the structure of this section and the presentation of different approaches.

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individual level; summing over all individuals or households give 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. That is to say, they are *ex post* assessments of the extent to which a negative shock causes a household to deviate from expected welfare. Put another way, they measure *ex post*, 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. Specifically, 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; i.e.,

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

Pritchett, Suryahadi, and Sumarto (2000) extend the time horizon used by Chaudhuri, Jalan, and Suryahadi (2002) and Christiaensen and Subbarao (2001), 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(.) 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:

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

Given this definition and 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:

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

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. There is nothing novel in this critique - it applies equally to the headcount measure of poverty—and it is relatively straightforward to redress. For example, one could rewrite equation (1) as:

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

where $\Sigma_s\, p_s$ is the sum of the probability of all possible 'states of the world', s in period $t + 1$ and α, as in the Foster-Greer-Thorbecke (1984) poverty measures, is the welfare weight attached to the gap between the benchmark and the welfare measure. As described here, 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.

Note that although these two 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, we write:

$$VEP_t = (1/N) \Sigma_h^N \Sigma_s^S p_s \cdot I[c_{h,\,t+1} = z] \cdot [(z - c_{h,\,t+1})/z]^\alpha. \qquad (4)$$

Kamanou and Morduch (2002) propose a related measure, expressing vulnerability as expected *changes* in poverty rather than expected poverty *per se.* Specifically, they define vulnerability in a population as the *difference* between the expected value of a poverty measure in the future and its current value. As in (4) above, they attach weights to the deviations between the welfare measure and its benchmark. Again defining welfare in terms of consumption, their aggregate measure can be written as:

$$E(P_{at+1}) - (P_{at}) = 1/N \ S_h^{\ G_{t+1}} \ S_s^{\ S} \ P(s, c_{it+1}) \ ((z - c_{it+1})/z)^{\alpha}$$

$$- (1/N) \ \Sigma_i^{\ N} \ I[c_h = z] \cdot [(z - c_i)/z]^{\alpha}, \quad\quad (5)$$

where E is the expectation operator, s is a given state of the world for which the joint probability distribution with Y_{t+1} is $P(s, y_{it+1})$, and G_{t+1} is the number of poor households in the future period.

These measures of vulnerability share a number of strengths. First, they produce a number analogous to a measure of the incidence or severity of poverty. There can be occasions when such numbers are helpful. Consider a case where measured poverty is low but a substantial proportion of households have consumption just above the poverty line. Indonesia in the mid 1990s would be a good example of this. In this scenario, governments (and donors) might become complacent, assuming that poverty has been 'solved'. But if these households lying just above the poverty line are vulnerable to shocks, summary measures of vulnerability will be much higher, indicating that such complacency is misplaced. Here, activities should focus on mechanisms to reduce the likelihood of such shocks occurring and/or strengthen responses to these shocks. Second, if the characteristics of the vulnerable differ significantly from the poor, targeting the latter (for example, by using a proxy means tests that focuses on the determinants of poverty) will miss a significant group of households that are vulnerable to declines in living standards. Third, as explained in the next section, these approaches can all be implemented using a single round of cross-sectional data. So the data needs associated with this approach are less daunting than those that require panel data.

3.3 Vulnerability as Low Expected Utility (VEU)

Vulnerability as expected poverty measures have a somewhat perverse feature related to measuring the welfare consequences of risk. With $\alpha > 1$, the Foster et al. (1984) poverty measures attribute risk-aversion to households. However, these measure seem ill-suited to representing household risk attitudes (Ligon and Schechter 2002). Consider two possible scenarios. In the first scenario, 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! Second, the $P\alpha$ measure implies an absolute risk aversion of $(\alpha - 1)z/(z-c)$, where z is the poverty line, c is household consumption, and α is a nonnegative parameter. Even if $\alpha > 1$, so that households are risk-averse, this implies that households have increasing absolute risk aversion, which is contrary to empirical evidence on the risk preferences of poor households.

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 the household would not be considered vulnerable—z_{CE} is analogous to a poverty line—and the expected utility of consumption. As in Figure 2 and the measures of vulnerability as expected poverty, consumption of household, c_h, has a distribution that reflects different states of the world. So they write their measure of vulnerability as:

$$V_h = U_i(z_{CE}) - EU_h(c_h), \qquad (6)$$

where U_h is a weakly concave, strictly increasing function. Note that (6) can be rewritten as:

$$V_h = [U_h(z_{CE}) - U_h(Ec_h)] + [U_h(Ec_h) - EU_h(c_h)]. \qquad (7)$$

The first bracketed term, a measure of poverty, is the difference in utility at z_{CE} compared to household i's expected utility at c. The second term measures the risk faced

by household h. It can be further decomposed into covariate or aggregate[12] 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 (7) as:

$$V_h = [U_h(z_{CE}) - U_h(Ec_h)] \qquad\qquad \text{(Poverty)}$$
$$+ \{U_h(Ec_h) - EU_h[E(c_h|\mathbf{x_t})]\} \qquad\qquad \text{(Covariate or Aggregate risk)}$$
$$+ \{E\ U_h[E(c_h|\mathbf{x_t})] - EU_h(c_h)\} \qquad\qquad \text{(Idiosyncratic risk)} \qquad (8)$$

Lastly, (although Ligon and Schechter do not do this explicitly), note that by summing over all households, one can form an estimate of aggregrate vulnerability:

$$VEU = (1/N)\ \Sigma_h^N\ \{\ [U_h(z_{CE}) - U_h(Ec_h)] + \{U_h(Ec_h) - EU_h[E(c_h|\mathbf{x_t})]\} + \{\ EU_h[E(c_h|\mathbf{x_t})] - EU_h(c_h)\}\ \}\ \ (9)$$

Given limited resources available to policymakers or donors, one might wish to know if vulnerability largely reflects low asset levels, unfavorable settings or poor returns to assets—all of which are captured in the poverty term—or if it reflects shocks and the inability to cope with shocks, either covariate (the second term) or idiosyncratic (the third term). A further attraction of the Ligon-Schechter methodology is that it provides this information. Set against this are two concerns. First, equation (8) requires specifying a particular functional form for the utility function and this will affect the magnitudes calculated. While this criticism is correct, it holds true for all measures of vulnerability. Further, while the magnitudes are affected by changes in functional form, it appears that the relative magnitudes of the individual components are not so affected. A second concern *may* be more problematic. The units of measurement in (8) are units of utility (e.g., utils); a finding that $V_h = 0.25$ means that the utility of household h is 25 percent less than would be the case if all inequality of consumption (i.e., the first term in (8) and risks in consumption (i.e., the second and third terms in [8]) were eliminated. For many policymakers not used to the language of economics, this expression of magnitude may be difficult to understand.

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[12] Ligon and Schechter (2003) use the term aggregate rather than covariate—but their measure of aggregate risk—is described as the influence of changes in aggregate factors affecting all households.

3.4 Vulnerability as Uninsured Exposure to Risk (VER)

Our conceptual framework indicated that shocks could be either covariant (as in a rainfall shock) or idiosyncratic, such as illness. In the absence of effective risk management tools, such 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, is similar to the VEP and VEU approaches in that it is concerned with assessing welfare and welfare losses in a world where some risks are at best partially insured. 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. They differ from VEP and VEU measures in that there is no attempt to construct an aggregate measure of vulnerability.

As in Section 2, think of 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, $S(i)_{htv}$ idiosyncratic shocks. Further, 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 δ, β, γ, δ, and λ are vectors of parameters to be estimated and Δe_{htvt} is a household-specific error term capturing changes in the unobservable components of household preferences, we have:

$$\Delta \ln c_{htv} = \sum_i \boldsymbol{l}_i S(i)_{tv} + \sum_i \boldsymbol{b}_i S(i)_{htv} + \sum_{tv} \boldsymbol{d}_v (D_v) + \boldsymbol{d} X_{hv} + \Delta e_{hvt} \qquad (10)$$

For our purposes, the estimated values for λ and β in (10) are of especial interest because they identify the impact of covariate $S(i)_{tv}$ and idiosyncratic $S(i)_{htv}$ shocks respectively; if these shocks were fully insured against, λ and β would equal zero. Put another way, these estimated coefficients provide an estimate of the magnitudes of these impacts 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. This is the approach taken by Tesliuc and Lindert (2002) who have a single cross-sectional survey. In their model, equation (11) below, the *level* of (log) consumption is determined by covariant—$S(i)_{tv}$—and idiosyncratic—$S(i)h_{vt}$

shocks—as well as fixed household characteristics such as location, age, sex, and education of the household head.

$$\ln c_{htv} = a + \sum_i I_i S(i)_{tv} + \sum_i b_i S(i)_{htv} + dX_{hvt} + e_{hvt} \qquad (11)$$

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

$$\ln c_{NS,htv} = a + dX_{hvt} + e_{hvt} \qquad (12)$$

and so the impact of shocks is the difference between (11) and (12).

A variant of equation (10) involves replacing $\sum_i I_i S(i)_{tv}$ and $\sum_i b_i S(i)_{htv}$ with $\Delta \left(\overline{\ln y_{vt}} \right)$—the growth rate in average community income—and $\Delta \ln y_{htv}$—the growth rate of household income, respectively. These variables can be thought of as the summation of *all* covariate and idiosyncratic shocks respectively and so we have:

$$\Delta \ln c_{htv} = a + b\Delta \ln y_{hvt} + g\Delta \left(\overline{\ln y_{vt}} \right) + dX_{hvt} + \Delta e_{hvt} \ . \qquad (13)$$

Much of the focus of the empirical literature on risk sharing in developing and developed countries alike has focused on testing the prediction derived under complete risk sharing which states that $b = 0$ (e.g., see Townsend 1994; Mace 1991; and Jacoby and Skoufias 1998). Although complete risk sharing is frequently rejected, the estimated values of b are generally low (or close to zero) which implies that the growth rate of consumption is related to the (contemporaneous) growth rate of income, but certainly less so than what one would expect under an alternative hypothesis (e.g., $b = 1$) as implied by complete autarky and the complete lack of any risk sharing tools. Higher estimated values of b are interpreted as signifying a higher covariance between income and consumption changes and thus a higher vulnerability of consumption to income risk (Amin, Rai, and Topa 2001).[13] Such results would provide *prima facie* evidence that

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[13] The same idea is also explored by Schechter (2001) for Bulgaria, and Ligon (2001) for India.

existing risk management mechanisms are doing a poor job in protecting households from income shocks. That said, there are a number of issues that should be borne in mind when considering this method.

It is not necessarily the case that households with a higher variance in income (or income growth) or a higher variance of consumption (or consumption growth) are less 'vulnerable'. Variance of income growth could reflect inter-temporal changes in leisure. However, Skoufias (1996) finds that in India, the female intertemporal elasticity of labor substitution is found to be significant but small (as in estimates for the United States, Blundell and MaCurdy 1999), with significant differences related to landownership and the production stage, which suggest that credit constraints limit intertemporal substitution across periods. The estimates for males are negative or zero suggesting that there are not strong labor-leisure tradeoffs.

Ligon and Shechter (2002) correctly point out that in 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 amongst different households. A 10 percent reduction in income of a millionaire and a destitute are treated equally. This is restrictive. However, this weakness can be redressed. For example, interacting $\Delta \ln y_{hvt}$ with household characteristics (such as indicator variables for age, sex, education of the head or household location) 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 (11) separately for different groups. For example, Hoddinott and Kinsey (2001) disaggregate their Zimbabwean sample by pre-drought livestock holdings. Again, this allows the impact of shocks to differ across groups.

Another drawback embodied by equations (10) and (13) is the assumption that positive and negative income shocks have symmetric effects. The factors that determine whether one can deal with positive shocks (including access to safe assets and savings instruments) compared to dealing with negative shocks (selling assets, receiving transfers, or obtaining credit) may be quite different in general and between households.[14]

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[14] This draws heavily from Dercon 2002.

While credit may be hard to obtain, savings (via livestock or grain stores) is likely to be easier. Thus, interpreting **b** 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 $\Delta \ln y_{hvt}$ with two covariates denoting absolute values of the size of positive and negative income changes.

4. ECONOMETRIC APPROACHES TO ESTIMATING VULNERABILITY

We now turn to consideration of econometric approaches to estimating vulnerability drawing on recent studies that have estimated the three approaches to vulnerability, VEP, VEU, and VER. At the outset, there are three commonalities across the approaches described here. First, while we describe methods used by different authors below, there is no reason why one could not "mix and match." So for example, a VEP measure such as that proposed by Chaudhuri, Jalan, and Suryahadi. (2002) could use the specification of consumption laid out by Tesliuc and Lindert (2002). Second, at the core of all these approaches is an econometric model that estimates a welfare measure. Third, while the examples described below use consumption as the welfare measure, there is no need these methods can easily be extended to nonconsumption measures such as education and health. This may be desirable for two reasons: a) such outcomes may be of interest in their own right; and b) it permits identification of shocks at the *individual* rather than household level. For example, Hoddinott and Kinsey (2001) use a variant of equation (10) to examine the impact of the 1994/95 drought on the heights of preschool children living in three resettlement areas in Zimbabwe.[15] For primary-school aged children for example, the relevant dependent variable could be the failure to enroll or delayed enrollment in school; interruptions in schooling or grade repetition or dropping out before completing primary school. For adolescents, relevant dependent variables could be withdrawing from school, unemployment or employment

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[15] Other studies using this approach to examine the impact of shocks on education and health include Alderman, Hoddinott and Kinsey (2003), Alderman et al. (2001), del Ninno and Lundberg (2002), Deolalikar (1996), Dercon and Krishnan (2000a), Foster (1995), Hoddinott and Kinsey (1999), and Rose (1999).

under exploitative conditions in labor market or onset of risky behaviors including exposure to HIV/AIDS.

4.1 Estimating Probabilities of Expected Poverty

Estimating the probability of expected poverty ($V_{ht} = Pr(c_{h, t+1} = z)$), 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 but such data are, for developing countries, virtually nonexistent. An important contribution of Chaudhuri, Christiaensen, and their co-authors is to show how such a distribution could be uncovered with access to only a single cross section.

Following Chaudhuri assume that consumption is determined by the following stochastic process:

$$\ln c_{ht} = \beta \mathbf{X_h} + e_h \qquad (14)$$

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. Note that (14) could be readily extended to include covariate and idiosyncratic shocks as outlined by equation (11). The variance of the disturbance term (σ^2_{eh}) is determined by:

$$\sigma^2_{eh} = t \mathbf{X_h} \qquad (15)$$

where τ is also a vector of parameters. Three-step feasible generalized least squares (Amemiya 1977) are used to estimate values of β_{hat} and t_{hat}. Sample STATA code needed to implement this method is available on request. These parameters, together with $\mathbf{X_h}$ can be used to calculate expected log consumption and the variance of log consumption:

$$E[\ln c_{ht} \mid \mathbf{X_h}] = \mathbf{X_h}\,\beta_{hat} \tag{16}$$

and

$$\text{Var}[\ln c_{ht} \mid \mathbf{X_h}] = \sigma^2_{eh\,hat} = \mathbf{X_h}\,\tau_{hat} \tag{17}$$

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 equal to 0.5), the probability that a household with characteristics $\mathbf{X_h}$ will be poor is given by:

$$v_{ht} = Pr(\ln c_h < \ln z \mid \mathbf{X_h}) = \Phi\,[(\ln z - \mathbf{X_h}\,\beta_{hat})\,/\,\sqrt{}\ \mathbf{X_h}\,\tau_{hat}]\ . \tag{18}$$

Chaudhuri, Christiaensen and others who implement this approach are careful to note that estimating the standard deviation of consumption using a single cross-section implies that cross-sectional variability proxies intertemporal variation (e.g., Chaudhuri, Jalan, and Suryahadi 2002, p. 8). That is, in a single cross-section, one can only estimate the variability of expenditures *across* households and that this variation mirrors consumption variability *over time.* This is a strong assumption as vividly illustrated in the risk and vulnerability assessment of Guatemala by Tesliuc and Lindert (2002). Their qualitative fieldwork indicated that natural disasters are a particularly serious risk in Guatemala. Some individuals reported that they had never fully recovered from losses incurred in the aftermath of the 1976 earthquake while others reported significant damage incurred in 1998 by Hurricane Mitch. However, there were neither serious earthquakes nor hurricanes in the survey year that Tesliuc and Lindert use to examine vulnerability. In this context, using cross-sectional variation from a "non disaster" year understates the level of consumption vulnerability. Conversely, had a household survey took place in a particularly "bad" year one might erroneously conclude that a greater proportion of households are vulnerable.

Kamanou and Morduch (2002) point out a number of additional problems with the use of the standard deviation as a measure of consumption variability; (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. In practice, while one can refine this measure by disaggregating by region, by income group, etc., the assumption of homogeneity still has to be made[16] and (2) in using the standard deviation as a measure of vulnerability, downside risk is weighed the same as upside risk. For these reasons, they adopt a different approach in estimating their measure of vulnerability, equation (5). They assume that the true distribution of possible outcomes in the next period for households y_{it+1} could be known. Because, however, the joint distribution of s and y_{it+1} is not known, the authors gene rate a distribution of possible future outcomes for households using bootstrap techniques, based on their observed characteristics and consumption fluctuations of "similar" households.

Box 1: The Kamanou-Morduch Bootstrap Method

Kamanou and Morduch (2002) use the following bootstrap method to generate their estimate of vulnerability: (1) Starting with the base year of a panel, they draw a large number (1000) of independent bootstrap samples (b); (2) With each bootstrap sample, construct a regression equation to predict the change in consumption based on its correlation with a set of household covariates; (3) Predict per capita expenditure of the future period for each household in each of the bootstrap samples by augmenting the linear part of the predicted value with a shock drawn at random from the empirical distribution of the regression residuals (these are Monte Carlo estimates of future period consumption); (4) Using these samples, compute $P^b_{\alpha t+1}$ for each b from 1 to 1000 then estimate $EP_{\alpha t+1}$ as the mean of the bootstrap estimates $P^b_{\alpha t+1}$. This is the Monte Carlo estimate of the future period's poverty measure obtained from the bootstrap sample; and finally (5) define the Monte Carlos bootstrap estimate of vulnerability for the population for the period ($t1$, $t2$) as $V_\alpha^{mcb} = P_{\alpha t2}^{mcb} - P_{t1}$. Vulnerability is the expected value of poverty $P_{\alpha t2}$ at time $t2$ generated using simulation methods, less the observed value of the poverty measure P_α at time $t1$.

4.2 Estimating Vulnerability as Low Expected Utility

As Ligon and Schechter (2003) note, estimating equation (8),

$$V_h = [U_h(z_{CE}) - U_h(Ec_h)] + \{U_h(Ec_h) - EU_h[E(c_h|\mathbf{x_t})]\} + \{E\,U_h[E(c_h|\mathbf{x_t})] - EU_h(c_h),$$

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[16] Relatedly, Deaton and Paxson (1994) demonstrate that within any given cohort the variance of consumption increases over time and this variance may differ across cohorts. This implies that at any given point in time any attempt to characterize the variance of consumption changes of households must take into consideration the age distribution of the population since different households are likely to be at different points in their life -cycle.

requires two prior steps: choosing a functional form for U_h and devising a way of estimating the conditional expectations, $E(c_h|\mathbf{x_t})$. With respect to the first issue, Ligon and Schechter (2003) suggest the following:

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

where $\tau > 0$. An attractive feature of this form is that t can be interpreted as 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)[17]:

$$E(c_h|\mathbf{x_t}) = \alpha_h + ?_t + dX_{hvt} + e_{hvt} \tag{19}$$

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

$$
\begin{aligned}
V_h = &\ [U_h(Ec) - U_h(Ec_{ht})] && \text{(poverty)} \\
&+ \{U_h(Ec_{ht}) - EU_h[E(c_{ht}|\mathbf{x_{vt}})]\} && \text{(covariate, aggregate risk)} \\
&+\{\ EU_h[E(c_{ht}|\mathbf{x_{vt}})] - EU_h[E(c_{ht}|\mathbf{x_{vt}}, \mathbf{x_{hvt}})] && \text{(idiosyncratic risk)} \\
&+\{\ EU_h[E(c_{ht}|\mathbf{x_{vt}}, \mathbf{x_{hvt}})] - EU_h(c_{ht}) && \text{(unexplained risk \&} \\
&&& \text{measurement error)} \quad \text{(20)}
\end{aligned}
$$

Equation (20) produces a measure of vulnerability expressed in utility units. Ligon and Schechter note that one could regress each component of (20) on household characteristics in order to determine the correlates of vulnerability.

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[17] Note, that had data been available, this could have been extended to include representations of covariate and idiosyncratic shocks.

4.3 Vulnerability as Uninsured Exposure to Risk

The literature on vulnerability as uninsured exposure to risk uses four variants of equations (10) and (13). These are:

$$\Delta \ln c_{htv} = \sum_{tv} \boldsymbol{d}_{tv}\left(D_{tv}\right) + \sum_{i} \boldsymbol{b}_{i} S(i)_{htv} + \boldsymbol{g}X_{hvt} + \Delta \boldsymbol{e}_{hvt} \tag{21}$$

$$\Delta \ln c_{htv} = \sum_{tv} \boldsymbol{d}_{tv}\left(D_{tv}\right) + \boldsymbol{b}\Delta \ln y_{htv} + \boldsymbol{d}X_{hvt} + \Delta \boldsymbol{e}_{htvt} \tag{22}$$

$$\Delta \ln c_{htv} = \boldsymbol{a} + \sum_{i} \boldsymbol{l}_{i} S(i)_{tv} + \boldsymbol{b}\Delta \ln y_{hvt} + \boldsymbol{d}X_{hvt} + \Delta \boldsymbol{e}_{hvt} \tag{23}$$

$$\Delta \ln c_{htv} = \boldsymbol{a} + \boldsymbol{b}\Delta \ln y_{hvt} + \boldsymbol{g}\Delta\left(\overline{\ln y_{vt}}\right) + \boldsymbol{d}X_{hvt} + \Delta \boldsymbol{e}_{hvt} \tag{24}$$

All four 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 (23) 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 (i.e., exogenous changes in "settings") common to all households within any given community and survey round.[18] As changes in consumption are expressed in logarithms, they also account for potential differences in the round to round inflation rate across communities. Shocks can be represented in a variety of ways. For example, Dercon and Krishnan (2000a, 2000b) use household survey data from Ethiopia that contains self-reported indices of the severity of a variety of idiosyncratic shocks to agriculture. These include: farm-specific experience with rainfall; nonrainfall climatic shocks (frost damage, storm damage etc); pest, animal and weed damage; crop disease; and lack of water or grazing for livestock. In addition, they include adult illness or death as shock variables. In Skoufias (2002a) uses self-reports of being owed wages, on forced leave or being unemployed as idiosyncratic shocks affecting changes in consumption in Russia while Harrower and Hoddinott (2003) and

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[18] Including the community/round interaction dummies is equivalent to deviating all variables from their respective community/round mean. For more detailed discussion of this equivalence see Deaton (1997).

Skoufias (2002b) include losses resulting from theft as idiosyncratic shocks; Hoddinott and Quisumbing (2003) describe a series of techniques for collecting information on idiosyncratic shocks.

Section 4.4 (below) notes several limitations associated with the 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 (22). However, a problematic feature of estimating equation (22) 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. Where much household production is also consumed, this measurement error affects both the left and right hand side of equation (22) so that the direction of this bias is unclear. 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 (22) over equation (21).

Equations (23) and (24) provide two methods for focusing attention on consumption variability arising from covariant risk. Analogous to (21), an alternative strategy is to include representations of positive and negative covariant shocks as regressors, as is done in (23). 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 as do Fafchamps, Udry and Czukas (1998) who study whether livestock are a mechanism for smoothing consumption in Burkina Faso. Equation (24) 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 $\Delta\left(\overline{\ln y_{vt}}\right)$. In a purely autarkic world, where there is no pooling of resources

and risk sharing, the growth rate in the average community income should have no impact on the growth rate of consumption of any one household. 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 $\Delta\left(\overline{\ln y_{vt}}\right)$ into positive and negative changes.

It is important to note that the data requirements associated with the estimation of (21) and especially (22), (23) and (24) 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. Moreover, 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.[19] To the extent that repeated observations per household in panel survey do not exceed two or three, one may have to settle with estimating the degree of consumption insurance for groups of households with a groups defined by some observable (and preferably time invariant) characteristic.

4.4 Generic Issues

Before continuing, it is helpful to note briefly a number of generic issues common to all these quantitative assessments of vulnerability.

4.4.1 Data

The quality and form of household data have a strong bearing on the types of analysis that can be undertaken. As will be clear from the material presented in the previous sections, the scope of risk and vulnerability assessment is greatly enhanced if longitudinal household data are available. Relying on a single cross-sectional survey

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[19] Further, the higher the number of time observations per household the lower the variance of the estimated coefficient β.

requires the analyst to make strong assumptions; for example, that the standard deviation of consumption derived from a single cross-section implies that cross-sectional variability proxies intertemporal variation, see below, or that there is no correlation between observed shocks and unobservable household characteristics that are captured in the disturbance term. However, this should not be taken to imply that longitudinal data are both necessary and sufficient for these assessments.

First, longitudinal data are time consuming to collect. There collection requires strong data documentation skills (so that interviewers can find individuals and households in order to reinterview them) in addition to well-trained and disciplined survey team who are able to persist in tracking down hard-to-find households or individuals. In the absence of careful fieldwork, nonrandom attrition results which potentially destroys the value of collecting longitudinal data in the first place. Particular care must also be taken to ensure that data collected in different survey rounds are comparable as are the protocols associated with the collection of that information. While neither problem is insurmountable, as evidenced by the increasing number of longitudinal data sets in developing countries, it is important to recognize that there are costs as well as benefits associated with their collection. Second, carefully collected cross-sectional data can reveal much about risk and vulnerability, particularly if they are augmented by use of secondary sources, community and qualitative fieldwork. The companion document to this paper—Hoddinott and Quisumbing (2003) provides details on these techniques.

4.4.2 Attributing Causality

There are two points that we emphasize here. The first is to note that 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 that similar problems in the context of obtaining information on health shocks and 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 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, p. 107) 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 (2000b) suggest checking such self-reported 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.

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.

4.4.3 Selective Attrition or "Survivorship Bias"

Consider a village in which households reside on either side of a river. The river floods, but this only affects households on one side. Most preschoolers in these households contract diarrhea and subsequently die; preschoolers on the unaffected side of the river experience no adverse consequences to their health. Subsequently, a research team visits the village and undertakes a survey. Focusing only on surviving children, analysis of such data would likely lead to the conclusion that the flood had minimal effect on child health but this analysis presents a biased view because it ignores the flood's impact on those who did not survive to be surveyed. This is an example of selective attrition or "survivorship bias." Selective attrition is highly problematic in single cross-sectional studies unless these include a recall component. Longitudinal data offer more scope for addressing this concern.[20] Consider the following model:

$$Y_t = b_0 + b_1 X_t + U_t \quad (Y_t \text{ observed only if } A_t^* < 0), \tag{25}$$

$$A_t^* = b_2 + b_3 X_t + b_4 Z_t + U^*_t. \tag{26}$$

Relation (25) is the model of interest. The outcome variable, Y_t, is observed only for a subset of the entire sample, those for whom the latent index variable, A_t^*, is less than zero. Relation (26) represents a selection function depending on (possibly) the same independent variables in (25) as well as some additional ones. In practice, we do not typically observe (26) but only an indicator of whether an observation is selected or not, i.e., $A_t = 1$ ($A_t^* < 0$) if selected and $A_t = 0$ ($A_t^* \geq 0$) if not. As suggested by the narrative that begins this section, if there is correlation between the error terms U_t and U^*_t, estimation of (25) ignoring (26) leads to inconsistent parameter estimates of b_1.

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[20] This discussion draws on Martorell et al. (2000).

Fitzgerald, Gottschalk, and Moffitt (1998) and the references they cite provide further details on testing for attrition bias in longitudinal data and how to redress this where attrition is found to be nonrandom.

5. USING VULNERABILITY MEASUREMENT TO INFORM POLICY: EMPIRICAL EXAMPLES

Section 3 outlines three approaches to measuring vulnerability. Complementary analysis based on these approaches can be used to answer four questions of interest to the practitioner or policymaker who is interested in reducing vulnerability: (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 household 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 (14),

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

As explained above, $\mathbf{X_h}$ 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, (14) 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 (14) 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 type 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.

The literature reviewed in Section 3 suggests three additional approaches:

(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 (into deciles, into "poor" and "most vulnerable," etc.) 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) If using the "vulnerability to risk exposure" approach, estimate the variability of consumption in response to idiosyncratic shocks for subgroups of the population.

Chaudhuri and Christiaensen (2002) provide an example of the first approach. Using the method of measuring vulnerability proposed by Chaudhuri (2000) and Chaudhuri, Jalan, and Suryahadi (2002), they present selected characteristics of the poorest 26 percent and the most vulnerable 26 percent of survey households in Southern China, based on rural household survey data from 1985-1990. The characteristics of the poor are remarkably consistent with the characteristics of the vulnerable: large family sizes, high dependency ratios, illiteracy, location in counties with low provision of public services and poorer regions of the country. Table 2 gives a flavor of their results.

Tesliuc and Lindert (2002) use a variant on this method. Using a single cross-sectional household survey from Guatemala, they calculate a headcount (P0) poverty measure as well as a headcount vulnerability measure based on the Chaudhuri (2000)

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Table 2: Comparing characteristics of the poor and the vulnerable in southern China

	Poorest 26%	Most vulnerable 26%
Household characteristics		
Average family size	6.39	6.19
Fraction with high dependency ratio	56	53
Fraction with high illiteracy rates	28	32
Location and ethnicity		
Guangdong: coast, plain	0.5%	0.1%
Guangdong: inland, hill	3.3%	1.0%
Guangxi: minority, mountainous	8.9%	10.2%
Yunnan: Han, mountainous	7.9%	11.2%
Yunnan: minority, mountainous	4.5%	6.4%
County characteristics		
Road coverage in county (sq. km)	625	607
Medical personnel	347	308
Proportion of cultivated area irrigated	38.8	35.5
Infant mortality rate (per 1000)	47	50
Illiteracy rate in county	40	42
Average per capita consumption	200	225

methodology. Next, they compare poverty and vulnerability within different subgroups of the population: area of residence (rural or urban); region (Guatemala City, north, north-east, north-west, central, south-east, south-west and Peten); ethnicity, gender, age and education of household head; and sector of occupation of head. Along some dimensions, characteristics of the poor and vulnerable were comparable (e.g., area of residence age and sex of head) whereas others exhibited marked differences. For example, headcount vulnerability was twice as high as headcount poverty in Guatemala City and four times as high as headcount poverty amongst individuals working in the mining sector.

Chaudhuri and Christiaensen (2002) provide a third example. Defining a household as vulnerable if it is more likely than not to be poor at least once during the next three years, they compare the incidence of vulnerability to the incidence of poverty within various segments of the population. A selection of their results is presented in Table 3; this ranks regions in southern China based on observed poverty in 1985 and by their definition of vulnerability; a higher rank means a higher poverty incidence or a higher ratio which is vulnerable to poverty. Table 3 shows that poverty and vulnerability rankings do not necessarily coincide. Minority areas in the plains of Yunnan, for

example, have lower poverty rankings (3rd lowest) compared to vulnerability rankings (7th lowest). Also useful is the ratio of the vulnerable to the poor population that is given in the last column of Table 3. In Yunnan, there are 2.3 times more vulnerable people than poor people. Han areas in the plains of Guangxi have high poverty rates (11th lowest out of 21) but lower vulnerability rankings (8th lowest). Minority areas in the mountains of Yunnan rank 12th in terms of poverty, but a high 17th in terms of vulnerability. The ratio of vulnerable to poor is 2.23. Such comparisons may enable policymakers to distinguish between the targets of poverty-prevention and poverty-reduction programs. Using this example, programs which reduce the probability of becoming poor are probably better targeted to areas with higher ratios of vulnerable to poor (minority areas in the plains and mountains of Yunnan), while programs targeted to structural poverty are better placed in areas with high poverty ranking but low vulnerability ranking.

Table 3: Rankings of poverty and vulnerability within regions of southern China

Region	Observed poverty, 1985		Fraction vulnerable to poverty within three years		Ratio of vulnerable to poor
	Rank	Rate	Rank	Fraction	
Guangdong: inland, plains	1	0.043	1	0.020	0.462
Guangdong: coastal, plains	2	0.078	2	0.049	0.625
Yunnan: minority area, plains	3	0.098	7	0.230	2.333
Guangdong: inland, hilly	4	0.100	3	0.074	0.745
Yunnan: Han, plain	5	0.126	6	0.222	1.756
Guangdong: coastal, hilly	6	0.134	4	0.075	0.556
Guangdong: inland, mountainous	7	0.164	5	0.187	1.143
Yunnan: Han, hilly	8	0.220	9	0.368	1.675
Guangxi: minority area, plain	9	0.225	10	0.405	1.800
Guangxi: Han, hilly	10	0.236	11	0.431	1.826
Guangxi: Han, plain	11	0.245	8	0.367	1.500
Yunnan: minority area, mountainous	12	0.257	17	0.572	2.232
Guangxi: Han, mountainous	13	0.265	13	0.493	1.864
Yunnan: minority area, hilly	14	0.266	12	0.469	1.765
Guizhou: minority area, hilly and plain	15	0.282	14	0.500	1.773
Guangxi: minority area, hilly	16	0.306	16	0.563	1.844
Yunnan: Han, mountainous	17	0.313	20	0.664	2.125
Guangxi: minority area, mountainous	18	0.371	19	0.605	1.632
Guizhou: Han, hilly and plain	19	0.411	15	0.539	1.313
Guizhou: Han, mountainous	20	0.425	18	0.604	1.420
Guizhou: minority area, mountainous	21	0.502	21	0.740	1.475

Source: Chaudhuri and Christiaensen (2002), Rural Household Survey 1985-90.

Ligon and Schechter (2002) provide an example of the second approach. They regress each element of vulnerability on a set of observable household characteristics. They find that households headed by an employed, educated male are less vulnerable to aggregate shocks than are other households. They also find that the correlates of vulnerability are extremely similar to the correlates of poverty; moreover, the correlates of aggregate risk are the same as the correlates of poverty. This is not surprising since aggregate shocks are, by definition, the same for all households, and so poorer households will experience a greater impact on their utility from this component of risk.

Skoufias (2002a) provides an example of the third approach. In order to ascertain whether shocks have different impacts on different groups, he estimates a slightly amended version of equation (24)

$$\Delta \ln c_{htv} = \sum_{tv} \delta_{tv}(D_{tv}) + \beta \Delta \ln y_{htv} + \gamma Z + \delta(Z * \Delta \ln y_{htv}) + \gamma X_{htv} + \Delta \varepsilon_{htv} \qquad (22')$$

where Z is a binary variable identifying households with a particular observed characteristic. In this specification the sign and size of the parameter δ identifies the extent to which there is higher or lower covariation between income and consumption changes in the group of households with this specific characteristic relative to the reference group of households without this characteristic. Along similar lines the t-value associated with δ allows one to test whether this difference is significant.

Using longitudinal data from Russia, Skoufias (2002a) defines Z to include prior poverty status,[21] whether the household is in a rural or urban area, whether the household resides in one of the eight regions covered by the survey, whether there are children between 0 and 6 years of age in the household, whether the household head is retired, whether the household head is a female, the type of occupation of the household head, and whether the household owns any land.[22] He finds that in the survey round collected soon after the August 1998 crisis, households with younger children were found to be

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[21] A household is classified as poor in round V (or round VIII) if its per capita consumption expenditures is less that or equal to the 30th percentile of per capita consumption expenditures in round V.

[22] Although it is possible that some of these characteristics may change over time, they are treated as time invariant and the information of the initial observation of each household is used in order to assign values for the indicator variable Z.

less vulnerable (perhaps as a consequence of the child allowances they receive) while female households were more vulnerable. Harrower and Hoddinott (2002) use the method suggested by Skoufias but in a much different setting, the semi-arid Zone Lacustre region of Mali. They include a rich set of household characteristics in their version of the vector Z: relative poverty status (as measured by asset holdings in the first survey round); representations of the occupation, ethnicity, sex and age of the household head, household size. While none of these covariates have explanatory power, they do find that income shocks have larger effects on consumption amongst households without access to irrigation infrastructure.

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 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 (2000b), who use three rounds of longitudinal data from the Ethiopia Rural Household Survey, provide such an example. Their dependent variable is (log) household consumption per equivalent adult net of food aid and food for work. Using a 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.

Covariant shocks include village level rainfall, prices and wages. Idiosyncratic shocks include self-reported (at the household level) rainfall shocks, crop damage, livestock disease and problems with access to grazing or water for livestock. They find that both idiosyncratic and aggregate shocks matter. Village level rainfall, the crop damage assessment, and the livestock disease variables are strongly significant and of the right sign: negative (positive) shocks have negative (positive) effects on consumption. Seasonal effects are also important: households increase consumption in peak labor periods when returns to labor are high, and reduce it in response to seasonal price changes.

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:

$$R_{htv} = \sum_{tv} \delta_{tv}(D_{tv}) + \sum_i \beta_i S(i)_{htv} + \gamma X_{hvt} + \varepsilon_{hvt} \qquad (27)$$

or

$$\Delta R_{htv} = \sum_{tv} \delta_{tv}(D_{tv}) + \sum_i \beta_i S(i)_{htv} + \gamma X_{hvt} + \Delta \varepsilon_{hvt} \; , \qquad (27a)$$

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. If R_{htv} and ΔR_{htv} are zero/one variables, then equation (27) is estimated as a logit or probit; equation (27a) is estimated as a fixed effects logit. If they are continuous variables, they are estimated using OLS techniques. Note that 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, a 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 (27) can be estimated using a single cross-sectional data set whereas (27a) requires longitudinal data. However, there may be location specific characteristics which 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 (27) therefore runs the risk that because $S(i)_{htv}$ (observed shocks) are correlated with e_{hvt}, estimates of b_i are biased. Household level fixed effects regressions overcome this by differencing at the household level—so as to purge the estimates of time invariant unobservables—but 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 must be dropped before estimation.

Table 4 provides an example of this approach using longitudinal household data from Mali, Russia, Bangladesh, and Ethiopia (Skoufias and Quisumbing 2002). The dependent variables are the use of the risk management mechanism so that each column represents a separate regression. Given the data available across these four studies, these mechanisms are divided into the following categories: drawing down assets (i.e., employ a risk management mechanism that was put into place *ex ante*); access capital markets, reallocate labor, and access private or public transfers (examples of *ex post* responses). For each data set, we then describe the way in which these risk management mechanisms are described in the data. Estimates are based on the inclusion of all shocks; each row represents an observed idiosyncratic shock so that a + sign indicates that a given shock was associated with an increased likelihood that the household undertook some action in response to that shock (going into debt, household members out-migrating etc) and a – sign indicates that a given shock was associated with a reduced likelihood that the household undertook some action in response to that shock.

The first two panels of Table 4 present the results from Mali and Russia, which both employ fixed-effects logit. In the Bangladesh and Ethiopia case studies, in all

Table 4: Household responses to idiosyncratic shocks, results from four countries

	Mali: Estimator is fixed effects logit					
	Dependent variables: ΔR_{htv}					
General description of risk management mechanism	**Draw down assets**	**Access capital markets**	**Reallocate labor**	**Access private transfers**		**Access public transfers**
Specific risk management mechanism available from survey	**Household made net livestock sales**	**Household became net debtor**	**At least one household member outmigrated**	**Receive remit-tances**	**Receive food gifts from family, friends**	**Not tested**
Observed shock						
Crops attacked by insects	+	+	+	+	+	
Household unable to cultivate all land	+	-	-**	+	+	
Livestock lost because of theft or death	+**	+**	+**	-	+**	
At least one member of household lost productive time due to illness	-	-**	-	+	+	

	Russia: Estimator is fixed effects logit					
	Dependent variables: ΔR_{htv}					
General description of risk management mechanism	**Draw down assets**	**Access capital markets**	**Reallocate labor**		**Access private transfers**	**Access public transfers**
Specific risk management mechanism available from survey	**Household sold assets in last three months**	**Household borrowed money**	**Engage in informal activities**	**Get 2nd job**	**Not tested**	**Received transfers**
Observed shock						
Household owed wages	-	+**	+	+**		-
Adult household member on forced leave	-	-	+	+**		+
Adult household member unemployed	+	+**	-**	-**		+

(continued)

Table 4 (continued)

	Bangladesh: Estimator is fixed effects Dependent variables: ΔR_{htv}					
General description of risk management mechanism	**Draw down assets**	**Access capital markets**	**Reallocate labor**	**Access private transfers**	**Access public transfers**	
Specific risk management mechanism available from survey	**Household made net asset sales**	**Household became net debtor**	**Not tested**	**Received remittances**	**Received food for educat[n]**	**Received relief**
Observed shock						
Log value of livestock losses	+	-		-	+	+
At least one female household member lost productive time due to illness	-	-		+	+	-
At least one male household member lost productive time due to illness	-*	+		+	+	+

	Ethiopia: Estimator is fixed effects Dependent variables: ΔR_{htv}						
General description of risk management mechanism	**Draw down assets**	**Access capital markets**	**Reallocate labor**	**Access private transfers**	**Access public transfers**		
Specific risk management mechanism available from survey	**Not tested**	**Household became net debtor**	**Women engaged in income earning activities**	**Not tested**	**Food for work**	**Receive free food**	**Receive cash transfers**
Observed shock							
Household level rainfall shocks		+	+		-	-	-
Nonrainfall crop shocks (e.g., crop diseases)		+**	-		+**	+**	-**
Livestock suffer from disease		+	-		-	+	+
Lack of grazing land or water		+	+		+	+	+
Days lost due to illness		+*	+		-	-	-

Note: * Significant at the 10 percent level; ** Significant at the 5 percent level. All shock variables are included simultaneously in the regressions, and significance levels are based on standard errors corrected for heteroscedasticity using the Huber-White method. For further details, see Skoufias and Quisumbing (2002).

survey periods a large number of households made use of coping mechanisms such as incurring debt, selling assets, receiving transfers from friends or relatives, and participating in public safety net programs. Thus, the lack of variation in terms of entry and exit into programs or types of coping mechanisms made fixed effects logit estimation infeasible as it led to the exclusion of the majority of the sample from estimation. In these two studies, the dependent variables were expressed in levels, net debt, net asset sales, remittance receipts, and public transfers and OLS fixed effects estimation procedures were used instead. Looking across these four studies, differences in country settings and institutional context are immediately apparent in the use of risk management mechanisms given shocks.

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 risk management mechanisms

| Responses | Welfare impacts of shocks | |
	Not significant	Significant
Private *AND* Public	**A**: Possibly successful SRM (but think about balance between public and private responses)	**B:** Existing SRM mechanisms are inadequate
Private *BUT NO* Public	**A**: Possibly successful private SRM (think about role of public interventions)	**B:** Private SRM mechanisms inadequate; consider role of public
NO Private *BUT* public	**A**: Possibly successful public SRM (think about role of private responses)	**B:** Public SRM mechanisms inadequate; but why no private response
NO Private, *NO* 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, though 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. This diversification may come at high cost. Walker and Ryan (1990) find that in semi-arid areas of India, households may sacrifice up to 25 percent of average incomes to reduce exposures to shocks. 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 form school when there are shortfall 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 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 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, only feasible with longitudinal data is to stratify the sample on the basis of pre-shock characteristics that are assumed to represent ex ante risk management mechanisms. The study by Hoddinott and Kinsey (2001) described earlier provides 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 including the 1994/95 drought. Again 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. These results are shown in Table 6.

Table 6: Drought effects on child growth by pre-drought wealth levels in Zimbabwe

Variable	Child resides in household with pre-drought livestock holdings	
	Below the median	**Above the median**
Child aged 12-24 months in period	-2.202	-1.281
following 1994/95 drought	(1.795)*	(0.844)
Mother's education	0.843	-0.542
	(1.748)*	(1.090)
Mother's education squared	-0.075	0.014
	(1.713)*	(0.353)

Notes: Specification includes, but does not report, the following covariates: initial child height, child age, sex and duration of observation, maternal age and relationship to head, household assets (livestock and land quality), year and village fixed effects. * Significant at the 10 percent level.

This produces a stark finding, namely that the 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 "toolkit" provides quantitative tools to practitioners who want to undertake risk and vulnerability assessments using household 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 are summarized in Table 7.

Table 7: Approaches to vulnerability

	Vulnerability as expected poverty	Vulnerability as expected low utility	Vulnerability as uninsured exposure to risk
Definition	Vulnerability of household h at time t, V_{ht} is the *probability* that the household's welfare (consumption) at time $t + 1$ ($c_{ht + 1}$) will be below the benchmark (consumption poverty line, z): $V_{ht} = Pr(c_{h, t + 1} = z)$	Vulnerability is the difference between the utility derived from some level of certainty-equivalent consumption, z_{CE} at and above which the household the household would not be considered vulnerable and the expected utility of consumption. $V_h = U_i(z_{CE}) - EU_h(c_h)$ or $V_h = [U_h(z_{CE}) - U_h(Ec_h)] + [U_h(Ec_h) - EU_h(c_h)]$	An *ex post* assessment of the extent to which a negative shock caused a welfare loss
How calculated	1. Predict consumption for each household. 2. Derive the variance of consumption for each household. 3. Make assumptions regarding the distribution of consumption, the poverty threshold and the threshold probability value above which a household is considered vulnerable.	1. Make an assumption regarding the functional form regarding U. 2. Specify a conditional expectation of consumption Ec_h as a function of covariate and idiosyncratic/household characteristics 3. Calculate the two parts of the vulnerability measure (the risk component can be further broken down into covariate, idiosyncratic and unexplained/measurement error components).	1. Define Δlnc_{htv} as the change in log consumption between t and $= t-1$, $S(i)_{tv}$ denote covariate shocks, $S(i)_{htv}$ idiosyncratic shocks, D_v be community dummy variables, X household characteristics, d, b, γ, d, and λ are parameters to be estimated and $\Delta\epsilon_{htv}$ is the error term 2. Estimate: $\Delta lnc_{htv} = \lambda S(i)_{tv} + b S(i)_{htv} + d D_v + dX + \Delta\epsilon_{htv}$
Advantages	• Produces a "headline" vulnerability figure • May identify households "at risk" who are not poor • Relatively straightforward to calculate • Can be estimated with a single cross-section	• Not vulnerable subject to the perverse implications of the VEP measure • Provides clean disaggregation between vulnerability due to poverty and vulnerability due to uninsured risk • Can also be used to calculate an aggregate measure of vulnerability	• Provides *prima facie* evidence that existing risk management mechanisms are doing a poor job in protecting households from income shocks. • Can indicate whether covariate or idiosyncratic shocks are the principal cause of welfare losses. • Can be adapted to determine whether shocks have different effects across different groups. • Easy to estimate.

(continued)

	Vulnerability as expected poverty	Vulnerability as expected low utility	Vulnerability as uninsured exposure to risk
Disadvantages	• *If* estimated using a single cross-section, must make strong assumption that cross-sectional variability captures temporal variability • Can, in principal, generate 'perverse' policy recommendations, that exposing households to increased levels of uninsured risk does not make them more vulnerable, and could make them less vulnerable	• Probably the hardest measure to calculate • Units of measurement somewhat difficult to convey to individuals with little formal training in economics. A	• Does not produce a "headline" vulnerability estimate (though it can be adapted to estimate "cost of shocks") • Is *ex post* rather than *ex ante* • Really requires panel data (with three or more rounds) to be credibly estimated
Sample reference	Chaudhuri, S., et.al. 2002. "Assessing Household Vulnerability to Poverty: A Methodology and Estimates for Indonesia," Columbia University Department of Economics Discussion Paper No. 0102-52.	Ligon, E. and L. Schechter, 2003, "Measuring vulnerability" *Economic Journal*.	Skoufias, E. and A.R. Quisumbing (2002) "Consumption Insurance and Vulnerability to Poverty" Draft, IFPRI.

These approaches are described more fully in Section 3; Section 4 provides a complementary discussion of the econometric issues associated with their implementation. As a result, 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 (S*ection 5.3*), and
- What gaps exist 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 that 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.

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Stata Programs for Risk and Vulnerability Assessment

This appending contains STATA programs corresponding to the three methods for risk and vulnerability analysis:

1. vep code: contains two programs estimating the vulnerability to expected poverty, from Luc Christaensen <lchristiaensen@worldbank.org> and Shubham Chaudhuri sc301@columbia.edu

    christiaensen.do
    vul-est-china.do

2. veu code: contains programs based on the Ligon-Schechter (Economic Journal, 2003) approach to measuring vulnerability as low expected utility (VEU). For questions regarding this approach, contact <ligon@are.Berkeley.edu>

    readme.txt
    sample.do
    sample.log
    vulncalc.ado
    vulncalc2.ado
    vulnerability.ado
    vulnerability.hpl

3. ver code: contains programs and data for estimating vulnerability as uninsured exposure to risk; the programs are from Quisumbing (2002a) on Bangladesh. For questions regarding this approach, contact <a.quisumbing@cgiar.org>

    bangla_risk.do
    bangla.log

Summary:

christaensen.do

```
**Program to calculate ex ante mean and variance of future consumption; only for
low rainfall areas**
**1997 expenditure variable regressed on 1994 variables; all variables cluster
averages**

*step 1: calculate ex ante mean*
capture log close
capture log using vuln1, replace
set more off
#delimit ;
reg ldaeex97_r hhsize depratio femhd plit mpfevmal
        toholnowae toholfert toholfertrshock numbanimae
        pocc6 pocc7 pocc8 shinc7 elec timmkt97
        rshock
if rural==1 & plowlnd<0.750& pmocc4<0.5 & cluster ~= 462 & cluster~=276 &
cluster~=770 & cluster~=872 & cluster~=969 & cluster~=967;
#delimit cr
predict res, residuals

*step2: calculate ex ante variance*
gen res2=res^2
gen lres2=ln(res2)
label variable lres2 "log (var log(reg defl exp97/ae)"

#delimit;
reg lres2 hhsize depratio femhd plit mpfevmal
        toholnowae toholfert toholfertrshock  numbanimae
        pocc6 pocc7 pocc8 shinc7 timmkt97
        rshock
if rural==1 & plowlnd<0.75 & pmocc4<0.5 & cluster ~= 462 & cluster~=276 &
cluster~=770 & cluster~=872 & cluster~=969 & cluster~=967;
#delimit cr
predict plnres2
label variable plnres2 "predicted ln squared predicted residuals"
outreg using vulnru040901h, bdec(5)replace
gen eplnres2=exp(plnres2)
drop res
predict res if e(sample), residuals
list cluster res if (res >  5 | res <-5) & res~=.

*step3: correct mean regression for heteroskedasticity
#delimit ;
reg ldaeex97_r hhsize depratio femhd plit mpfevmal
        toholnowae toholfert  toholfertrshock numbanimae
        pocc6 pocc7 pocc8 shinc7 elec timmkt97
        rshock
 [aweight=1/eplnres2]
if rural==1 & plowlnd<0.750 & pmocc4<0.5 & cluster ~= 462 & cluster~=276 &
cluster~=770 & cluster~=872 & cluster~=969 & cluster~=967;
#delimit cr
drop res
predict res if e(sample), residuals
list cluster res if (res >  5 | res <-5) & res~=.
outreg using vulnru040901h, bdec(5) append
drop res res2 lres2 plnres2 eplnres2
log close
```

```
**calculation of V0=probability of shortfall**

predict pldaeex97 if e(sample)
capture drop v0U
gen v0U=normprob((10.366-pldaeex97)/sdceplnres2)
label variable v0U"probability of expenditure shortfall in future(urban areas)"
drop res res2 lres2 plnres2 cplnres2 eplnres2 ceplnres2 sdceplnres2 pldaeex97
log close
```

vul-est-china.do

```
#delimit ;
cd c:/projects/vulnerability/china;
*log using logs/vulest-xs-china,replace;
************************************************************************
*VULEST-CHINA-XS-`2'.DO
*GENERATES CROSS-SECTIONAL VULNERABILITY ESTIMATES USING 19`2' CROSS-SECTION
FROM CHINA
*Syntax: do vulest-china-xs-`2' [using dataset] [year]
************************************************************************;
use data/`1', clear;
global year `2';
keep if year==19$year;

************************************************************************
* Define variable lists as macros                                     *
************************************************************************;
global rhscols    "fsize fsize2 depchi depkid depetn age age2 illfr prifr secfr
higfr staemp farm pcla pclasq
                  plains hills coast border minor revoln roads clinic medics
irrppn imr iltrcy";
global rhsvols    "fsize fsize2 depchi depkid depetn age age2 illfr prifr secfr
higfr staemp farm pcla pclasq
                  plains hills coast border minor revoln roads clinic medics
irrppn imr iltrcy";
global rhsvgls    "vgfsize vgfsize2 vgdepchi vgdepkid vgdepetn vgage vgage2
vgillfr vgprifr vgsecfr vghigfr vgstaemp vgfarm vgpcla vgpclasq
                  vgplains vghills vgcoast vgborder vgminor vgrevoln vgroads
vgclinic vgmedics vgirrppn vgimr vgiltrcy";
global rhscgls    "cgfsize cgfsize2 cgdepchi cgdepkid cgdepetn cgage cgage2
cgillfr cgprifr cgsecfr cghigfr cgstaemp cgfarm cgpcla cgpclasq
                  cgplains cghills cgcoast cgborder cgminor cgrevoln cgroads
cgclinic cgmedics cgirrppn cgimr cgiltrcy";

************************************************************************
* Initialization of key variables                                     *
************************************************************************;
capture drop one;
gen int one=1;
capture drop lcols; gen lcols=.;
capture drop stdlcols; gen stdlcols=.;
capture drop varlcols; gen varlcols=.;
capture drop vols1; gen vols1=.;
capture drop cols; gen cols=.;
capture drop varcols; gen varcols=.;

label var lcols "Predicted ln(c): OLS";
label var stdlcols "Predicted SD(ln(c)): OLS";
label var varlcols "Predicted V(ln(c)): OLS";
label var vols1 "Predicted 1-year vulnerability: OLS";
label var cols "Predicted c: OLS";
label var varcols "Predicted V(c): OLS";

capture drop eols; gen eols=.;
capture drop eolssq; gen eolssq=.;
capture drop lneolssq; gen lneolssq=.;
capture drop lnesqht; gen lnesqht=.;
```

4

```
capture drop varlcx$year; gen varlcx$year=.;
capture drop stdlcx$year; gen stdlcx$year=.;
capture drop lcx$year; gen lcx$year=.;
capture drop vx$year; gen vx$year=.;
capture drop vx${year}dum; gen int vx${year}dum=.;
capture drop cx$year; gen cx$year=.;
capture drop varcx$year; gen varcx$year=.;

label var lcx$year "Predicted ln(c): x$year";
label var stdlcx$year "Predicted SD(ln(c)): x$year";
label var varlcx$year "Predicted V(ln(c)): x$year";
label var vx$year "Predicted 1-year vulnerability: x$year";
label var cx$year "Predicted c: x$year";
label var varcx$year "Predicted V(c): x$year";
label var vx${year}dum "=1 if 1-year vulnerability > threshold";


*****************************************************************************
* Program: vulest
*****************************************************************************;
capture program drop vulest;
program define vulest;

local j = 1;
while `j' <= 4 {;

    display "Log consumption regression [OLS]: Province="`j';
    reg lc $rhscols if province==`j';
    capture drop xbht;
    predict xbht if province==`j';
    replace lcols=xbht if province==`j';
    drop xbht;
    replace stdlcols=_result(9) if province==`j';
    replace varlcols=stdlcols^2 if province==`j';
    replace vols1=normprob( (ln(zc85)-lcols)/stdlcols ) if province==`j';
    replace cols=exp( lcols + (0.5*varlcols) ) if province==`j';
    replace varcols=exp( (2*lcols) + varlcols)*(exp(varlcols)-1) if
province==`j';
    capture drop eht;

    predict eht if province==`j', res;
    replace eolssq=eht^2 if province==`j';
    sum eolssq if province==`j';
    replace lneolssq=ln(eolssq) if province==`j';

    display "Variance(ln(consumption)) regression [OLS]: Province="`j';
    reg lneolssq $rhsvols if province==`j';
    capture drop esqht;
    predict esqht if province==`j';
    sum esqht if province==`j';
    replace lnesqht=esqht if province==`j';

    quietly for var lneolssq one $rhsvols \ new vglnesq vgone $rhsvgls :
    gen Y=X/lnesqht if province==`j';
    display " Variance(ln(consumption)) regression [FGLS]: Province="`j';
    reg vglnesq vgone $rhsvgls if province==`j', noconstant;
    capture drop esqht;
    predict esqht if province==`j';
```

```
      sum esqht if province==`j';
      replace stdlcx$year=(exp(esqht*lnesqht))^0.5 if province==`j';
      replace varlcx$year=(exp(esqht*lnesqht)) if province==`j';
      display "No. of negative predicted variances:"; count if varlcx$year<0 &
province==`j';
      drop esqht vglnesq vgone $rhsvgls;

      quietly for var lc one $rhscols \ new cglc cgone $rhscgls :
      gen Y=X/stdlcx$year if province==`j';
      display "Log consumption regression [FGLS]: Province="`j';
      reg cglc cgone $rhscgls if province==`j', noconstant;
      capture drop xbht;
      predict xbht if province==`j';
      replace lcx$year=xbht*stdlcx$year if province==`j';
      replace vx$year = normprob( (ln(zc85)-lcx$year)/(varlcx$year^0.5) ) if
province==`j';
      replace cx$year=exp( lcx$year + (0.5*varlcx$year) ) if province==`j';
      sum cx$year if province==`j';
      local prdmean = _result(3);
      sum c if province==`j';
      local obsmean = _result(3);
      local scale = `obsmean'/`prdmean';
      replace varlcx$year = varlcx$year + 2*ln(`scale') if province==`j';
      replace vx$year = normprob( (ln(zc85)-lcx$year)/(varlcx$year^0.5) ) if
province==`j';
      replace cx$year=exp( lcx$year + (0.5*varlcx$year) ) if province==`j';
      replace varcx$year=exp( (2*lcx$year) + varlcx$year)*(exp(varlcx$year)-1)
if province==`j';
      drop xbht cglc cgone $rhscgls;

      local j = `j' + 1;
      };
drop one eols lnesqht eht;
drop if vx$year==.;
end;
***********************************************************************;
vulest;

*NOTE: check fit of regressions;
capture drop signlc; gen int signlc=cond(lcx$year>lc,1,-1) if lcx$year~=.;
capture drop signc;  gen int signc=cond(cx$year>c,1,-1) if cx$year~=.;
tab province signlc;
tab province signc;

tab pid, sum(vx$year) mean;
tab pid, sum(poor) mean;
tab pid, sum(vx$year) mean;

keep hid year lcx$year stdlcx$year varlcx$year cx$year varcx$year vx$year;
sort hid year;

save data/vulest-china-xs-`2',replace;
```

readme.txt

      This is a readme file for the code used to calculate vulnerability as defined by Ligon-Schechter (Economic Journal, 2003). If you are on a Windows machine, all four files, vulnerability.hlp

      vulnerability.ado vulncalc.ado and vulncalc2.ado, should be placed in the directory C:\ado\personal. If you are on a Linux machine the files can either be placed in the same directory with your data, or in your /ado/personal directory.

      vulnerability.hlp is the help file for the program. It is the source for what appears if you enter stata and type "help vulnerability". For help in using the code, it is much easier to type "help vulnerability" in stata and read the help file from there than it is to read vulnerability.hlp

      itself.

      vulnerability.ado is the code which prepares the data for vulnerability to be calculated, runs the bootstrap, and displays the results in a pretty fashion. It does not have any economic content.

      vulncalc.ado is the code called by vulnerability.ado which runs the linear consumption prediction equations to calculate the predicted consumptions from which vulnerability will be calculated.

      vulncalc2.ado is the code called by vulncalc.ado which uses the consumption predictions from vulncalc.ado to calculate vulnerability.

      vulntest.dta is a sample data set which one can use to try out and play around with the code.

      sample.do is a sample do file which tries out a lot of different options of the vulnerability code with the dataset vulntest.dta

      sample.log is a log file (from sample.do) which shows a lot of different options of the vulnerability code and the output they produce.

sample.do

```
# delimit;
use vulntest;
set logtype text;
log using sample, replace;
describe;
summarize;

** First we will just try it with three idiosyncratic risk variables.;
** The idiosyncratic risk variables are income, # of unemployed, and # of
pensioners.;
vulnerability myhhno month FoodCons Income nunemp npens;
drop poverty vulnerability *risk*;

** Then try it again for those under the age of 80.;
vulnerability myhhno month FoodCons Income nunemp npens if age<80;
drop poverty vulnerability *risk*;

** Then generate a fake weight (since ours is not weighted data.;
gen w=2;
vulnerability myhhno month Food Income nunemp npens [pweight=w];
drop poverty vulnerability *risk* w;

** Try it with log utility;
vulnerability myhhno month FoodCons Income nunemp npens, gamma(1);
drop poverty vulnerability *risk*;

** Try it with a poverty line of 1000;
vulnerability myhhno month FoodCons Income nunemp npens, z(2000);
drop poverty vulnerability *risk*;

** Try it with bootstrapped standard errors;
vulnerability myhhno month FoodCons Income nunemp npens, boot(1) nreps(200);
drop poverty vulnerability *risk*;

** Try it while running a regression afterwards.;
vulnerability myhhno month FoodCons Income nunemp npens, runregvar(sex age age2
educ2 educ3 educ4 res_type animals);
drop poverty vulnerability *risk*;

** Try it with a regression afterwards and bootstrapped standard errors.;
vulnerability myhhno month FoodCons Income nunemp npens, runregvar(sex age age2
educ2 educ3 educ4 res_type animals) boot(1) nreps(100);
drop poverty vulnerability *risk*;
log close;
```

sample.log

```
--------------------------------------------------------------------------------
log:/home/schechte/bulgaria/vulnstata/sample.log
log type:  text
opened on:  19 May 2003, 16:14:26

. describe;

Contains data from vulntest.dta
  obs:        27,444                          HHHEAD INFO+INCOME mrg=3
 vars:            15                          19 May 2003 15:40
 size:     1,180,092 (96.5% of memory free)
--------------------------------------------------------------------------------
            storage  display    value
variable name  type   format    label        variable label
--------------------------------------------------------------------------------
myhhno        float   %8.0g                   Household's ID
month         float   %8.0g                   Month processing
FoodCons      float   %9.0g                   Per-capita real food consumption
Income        float   %9.0g                   Per-capita real income
sex           byte    %8.0g                   1=male, 0=female
age           byte    %8.0g                   Age in years
age2          float   %9.0g                   Age squared
educ2         float   %9.0g                   1=Have only primary education
educ3         float   %9.0g                   1=Have only secondary education
educ4         float   %9.0g                   1=Have post-secondary education
res_type      byte    %8.0g                   1=town, 0=village
animals       byte    %8.0g                   1=Have FArm Animals
famsz         byte    %8.0g                   # of persons in HH
nunemp        byte    %8.0g                   # unemployed
npens         byte    %8.0g                   # pensioners
--------------------------------------------------------------------------------
Sorted by:

. summarize;

    Variable |      Obs        Mean    Std. Dev.      Min        Max
-------------+--------------------------------------------------------
      myhhno |    27444        1144     660.212        1       2287
       month |    27444         6.5    3.452115        1         12
    FoodCons |    27444    1602.147    721.6073  -2178.648   18673.72
      Income |    27444    2485.332    2075.603  -44780.16   81841.94
         sex |    27444    .7692756    .4213041        0          1
         age |    27444    54.59215    14.23752       18         94
        age2 |    27444    3183.003    1541.952      324       8836
       educ2 |    27444    .3482364    .4764201        0          1
       educ3 |    27444    .4153913    .4927984        0          1
       educ4 |    27444    .1265122    .3324317        0          1
    res_type |    27444    .6375164    .4807262        0          1
     animals |    27444    .4535418     .497846        0          1
       famsz |    27444    2.929092    1.395486        1         12
      nunemp |    27444    .2334937    .5370021        0          6
       npens |    27444    .8926541    .8643725        0          4

. ** First we will just try it with three idiosyncratic risk variables.;
. ** The idiosyncratic risk variables are income, # of unemployed, and # of
pensio
```

```
> ners.;
. vulnerability myhhno month FoodCons Income nunemp npens;


We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.


Means not taking into account sampling weights, even if specified

    Variable |     Obs       Mean   Std. Dev.       Min        Max
-------------+--------------------------------------------------------
vulnerabil~y |   27252   19.71556   42.23636   -69.0705   311.0009
     poverty |   27252   10.79002   36.99031  -72.17365   222.8564
        risk |   27252   8.925538   10.83183   .3450165   214.5512
      agrisk |   27252   2.642975   3.897174   .0296936   54.46426
   idrisktot |   27252   .0973372   1.025253  -15.47354   22.57245
      idrisk1 |   27252     .00169   .1720691  -2.190704   3.632782
      idrisk2 |   27252   .0512714   .8611174  -14.09906   20.78229
      idrisk3 |   27252   .0443758   .6354942  -20.65897    10.8821
    unexprisk |   27252   6.185226   10.13041  -62.80118   206.4046

. drop poverty vulnerability *risk*;

. ** Then try it again for those under the age of 80.;
. vulnerability myhhno month FoodCons Income nunemp npens if age<80;


We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.


Means not taking into account sampling weights, even if specified

    Variable |     Obs       Mean   Std. Dev.       Min        Max
-------------+--------------------------------------------------------
vulnerabil~y |   26484   19.77033   42.50547  -69.02962   311.5441
     poverty |   26484   10.82263    37.1889  -72.13687   223.2831
        risk |   26484   8.947698   10.90333   .3454762   214.8347
      agrisk |   26484   2.666454   3.970034   .0299644   54.91409
   idrisktot |   26484   .0921243   1.022813  -15.51709   22.56186
      idrisk1 |   26484   .0018988   .1731404  -2.175873   3.600693
      idrisk2 |   26484   .0524841   .8750778  -14.14224   20.88315
      idrisk3 |   26484   .0377415   .6153925  -20.28928   10.35576
    unexprisk |   26484    6.18912   10.18061  -63.15283   206.6683

. drop poverty vulnerability *risk*;

. ** Then generate a fake weight (since ours is not weighted data.;
. gen w=2;

. vulnerability myhhno month Food Income nunemp npens [pweight=w];


We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.
```

Means not taking into account sampling weights, even if specified

```
     Variable |     Obs       Mean   Std. Dev.       Min       Max
--------------+--------------------------------------------------------
vulnerabil~y |   27252   19.71556   42.23636   -69.0705   311.0009
      poverty |   27252   10.79002   36.99031  -72.17365   222.8564
         risk |   27252   8.925538   10.83183   .3450165   214.5512
       agrisk |   27252   2.642975   3.897174   .0296936   54.46426
    idrisktot |   27252   .0973372   1.025253  -15.47354   22.57245
       idrisk1 |   27252     .00169   .1720691  -2.190704   3.632782
       idrisk2 |   27252   .0512714   .8611174  -14.09906   20.78229
       idrisk3 |   27252   .0443758   .6354942  -20.65897    10.8821
     unexprisk |   27252   6.185226   10.13041  -62.80118   206.4046
```

. drop poverty vulnerability *risk* w;

. ** Try it with log utility;
. vulnerability myhhno month FoodCons Income nunemp npens, gamma(1);

We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.

Means not taking into account sampling weights, even if specified

```
     Variable |     Obs       Mean   Std. Dev.        Min       Max
--------------+--------------------------------------------------------
vulnerabil~y |   27252   8.802662   32.13586   -117.9135   127.5965
      poverty |   27252   5.113185   31.93771   -127.9187   117.2038
         risk |   27252   3.689477   3.028816    .277935   46.35791
       agrisk |   27252   .9407088   .7274334   .0534973   7.638054
    idrisktot |   27252   .0365532    .217101  -2.594193    2.33847
       idrisk1 |   27252   .0039203   .0588393  -.3120327   1.072567
       idrisk2 |   27252   .0150852   .1631187  -2.376717   2.053528
       idrisk3 |   27252   .0175477   .1433939  -3.140526   2.259781
     unexprisk |   27252   2.712215   3.067301  -8.144279   46.19448
```

. drop poverty vulnerability *risk*;

. ** Try it with a poverty line of 1000;
. vulnerability myhhno month FoodCons Income nunemp npens, z(2000);

We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.

Means not taking into account sampling weights, even if specified

```
     Variable |     Obs       Mean   Std. Dev.        Min       Max
--------------+--------------------------------------------------------
vulnerabil~y |   27252   49.28816   52.66975  -61.43017    412.528
      poverty |   27252    38.1578    46.1278  -65.29987   302.6097
         risk |   27252   11.13036   13.50755   .4302483   267.5504
       agrisk |   27252   3.295861   4.859877   .0370293   67.91827
    idrisktot |   27252    .121382   1.278516   -19.2959   28.14844
       idrisk1 |   27252   .0021076    .214574  -2.731873   4.530167
```

```
      idrisk2 |    27252    .0639366   1.073835   -17.58188   25.91605
      idrisk3 |    27252    .0553378    .7924766  -25.76224   13.57022
    unexprisk |    27252    7.713116   12.63286   -78.31461   257.3914
```

. drop poverty vulnerability *risk*;

. ** Try it with bootstrapped standard errors;
. vulnerability myhhno month FoodCons Income nunemp npens, boot(1) nreps(200);

We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.

The computer will count out every 50 repetitions...
Repetition #50
Elapsed time was 5 minutes, 8 seconds.
Repetition #100
Elapsed time was 5 minutes, 13 seconds.
Repetition #150
Elapsed time was 5 minutes, 16 seconds.
Repetition #200
Elapsed time was 5 minutes, 13 seconds.

Means not taking into account sampling weights, even if specified

```
      Variable |     Obs       Mean    Std. Dev.       Min        Max
-------------+-------------------------------------------------------
vulnerabil~y |    27252    19.71556   42.23636    -69.0705   311.0009
      poverty |    27252    10.79002   36.99031   -72.17365   222.8564
         risk |    27252    8.925538   10.83183    .3450165   214.5512
       agrisk |    27252    2.642975    3.897174   .0296936   54.46426
    idrisktot |    27252    .0973372   1.025253   -15.47354   22.57245
       idrisk1 |    27252      .00169    .1720691  -2.190704   3.632782
       idrisk2 |    27252    .0512714    .8611174  -14.09906   20.78229
       idrisk3 |    27252    .0443758    .6354942  -20.65897    10.8821
     unexprisk |    27252    6.185226   10.13041   -62.80118   206.4046
```


Bootstrapped confidence intervals for survey means of vulnerability measures.
These take into account sampling weights if specified.

```
Variable|Pop. Mean [ 90% Conf. Int.] [ 95% Conf. Int.] [ 99% Conf. Int.]
--------+----------------------------------------------------------------
vulnmean| 19.7156  [ 18.917, 20.467] [ 18.752, 20.635] [ 18.500, 20.858]
 povmean| 10.7900  [ 10.111, 11.351] [ 10.037, 11.559] [ 9.8508, 11.808]
riskmean| 8.92554  [ 8.5501, 9.2714] [ 8.4672, 9.3257] [  8.392,  9.372]
agrism~n| 2.64297  [ 2.4614, 2.8207] [ 2.4199, 2.8555] [ 2.3201, 2.9075]
idrism~n| .097337  [ .04774, .14681] [  .0412,  .1601] [ .02192, .18073]
idri1m~n|  .00169  [-.00506, .01103] [-.00601, .01267] [-.00916, .01795]
idri2m~n| .051271  [ .01499,  .0896] [ .00877, .09633] [  .0004, .12758]
idri3m~n| .044376  [ .01489, .08497] [ .01166, .08942] [ .00244, .09458]
unexri~n| 6.18523  [ 5.7938, 6.5517] [ 5.7439, 6.6139] [  5.620, 6.6736]
```

. drop poverty vulnerability *risk*;

. ** Try it while running a regression afterwards.;

```
. vulnerability myhhno month FoodCons Income nunemp npens, runregvar(sex age
age2
> educ2 educ3 educ4 res_type animals);


We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.


Means not taking into account sampling weights, even if specified

     Variable |      Obs        Mean    Std. Dev.        Min         Max
-------------+-----------------------------------------------------------
vulnerabil~y |    27252    19.71556    42.23636    -69.0705    311.0009
     poverty |    27252    10.79002    36.99031   -72.17365    222.8564
        risk |    27252    8.925538    10.83183    .3450165    214.5512
      agrisk |    27252    2.642975    3.897174    .0296936    54.46426
   idrisktot |    27252    .0973372    1.025253   -15.47354    22.57245
      idrisk1 |    27252      .00169    .1720691   -2.190704    3.632782
      idrisk2 |    27252    .0512714    .8611174   -14.09906    20.78229
      idrisk3 |    27252    .0443758    .6354942   -20.65897     10.8821
    unexprisk |    27252    6.185226    10.13041   -62.80118    206.4046


Non-bootstrapped vulnerability regression
                                               No. of obs =     2271
                                               R-squared  = .042026
----------------------------------------------------------------------
   Vulnerability| Coefficient
----------------+-----------------------------------------------------
            sex| 8.64701
            age|-.189981
           age2|-.001871
          educ2|-7.02601
          educ3|-18.6592
          educ4|-23.9718
       res_type| 6.39114
        animals|-7.38755
          _cons| 41.882
----------------------------------------------------------------------

Non-bootstrapped poverty regression
                                               No. of obs =     2271
                                               R-squared  =  .04676
----------------------------------------------------------------------
        Poverty| Coefficient
----------------+-----------------------------------------------------
            sex| 9.69158
            age|-.096511
           age2|-.002047
          educ2| -7.4160
          educ3|-17.1132
          educ4|-21.9561
       res_type| 5.45154
        animals| -7.6892
          _cons| 27.5851
----------------------------------------------------------------------
```

```
Non-bootstrapped risk regression
                                                    No. of obs =    2271
                                                    R-squared  =  .01177
------------------------------------------------------------------------
           Risk| Coefficient
---------------+--------------------------------------------------------
            sex|-1.04456
            age| -.09347
           age2| .000176
          educ2| .389997
          educ3|-1.54597
          educ4|-2.01574
       res_type| .939597
        animals| .301652
          _cons| 14.2965
------------------------------------------------------------------------


Non-bootstrapped aggregate risk regression
                                                    No. of obs =    2271
                                                    R-squared  = .031369
------------------------------------------------------------------------
 Aggregate Risk| Coefficient
---------------+--------------------------------------------------------
            sex| .139256
            age| .066173
           age2|-.000958
          educ2|-.697935
          educ3|-1.81176
          educ4|-2.06647
       res_type| .361855
        animals|-.624145
          _cons| 3.28288
------------------------------------------------------------------------


Non-bootstrapped total idiosyncratic risk regression
                                                    No. of obs =    2271
                                                    R-squared  =  .00646
------------------------------------------------------------------------
 Idiosync. Risk| Coefficient
---------------+--------------------------------------------------------
            sex| .092218
            age| .015359
           age2|-.000133
          educ2| .040886
          educ3| .029227
          educ4| .027158
       res_type| .107625
        animals|-.044495
          _cons|-.465803
------------------------------------------------------------------------
```

```
Non-bootstrapped idiosyncratic risk #1 regression
                                              No. of obs =    2271
                                              R-squared  = .008745
--------------------------------------------------------------------------
Idiosyn. Risk #1| Coefficient
----------------+---------------------------------------------------------
            sex|-.001153
            age| -.00242
           age2| .000028
          educ2| .029991
          educ3| .049495
          educ4| .047705
       res_type| .014007
        animals| .008031
          _cons|-.003028
--------------------------------------------------------------------------


Non-bootstrapped idiosyncratic risk #2 regression
                                              No. of obs =    2271
                                              R-squared  = .006364
--------------------------------------------------------------------------
Idiosyn. Risk #2| Coefficient
----------------+---------------------------------------------------------
            sex| .061916
            age|  .01149
           age2|-.000113
          educ2| .094937
          educ3|-.007414
          educ4| .034777
       res_type| .021546
        animals|-.081309
          _cons|-.275981
--------------------------------------------------------------------------


Non-bootstrapped idiosyncratic risk #3 regression
                                              No. of obs =    2271
                                              R-squared  = .005543
--------------------------------------------------------------------------
Idiosyn. Risk #3| Coefficient
----------------+---------------------------------------------------------
            sex| .031456
            age| .006289
           age2|-.000048
          educ2|-.084042
          educ3|-.012854
          educ4|-.055324
       res_type| .072072
        animals| .028783
          _cons|-.186795
--------------------------------------------------------------------------
```

```
Non-bootstrapped unexplained risk regression
                                              No. of obs =    2271
                                              R-squared  = .006784
-------------------------------------------------------------------------
Unexplained Risk| Coefficient
----------------+--------------------------------------------------------
            sex|-1.27604
            age|-.175003
           age2| .001268
          educ2| 1.04705
          educ3| .236566
          educ4| .023564
       res_type| .470117
        animals| .970292
          _cons| 11.4794

-------------------------------------------------------------------------


. drop poverty vulnerability *risk*;

. ** Try it with a regression afterwards and bootstrapped standard errors.;
. vulnerability myhhno month FoodCons Income nunemp npens, runregvar(sex age
age2
> educ2 educ3 educ4 res_type animals) boot(1) nreps(100);

We will ignore the 16 households with negative or 0 consumption or
missing data for consumption in at least one time period.
The computer will count out every 50 repetitions...
Repetition #50 Elapsed time was 7 minutes, 47 seconds.
Repetition #100 Elapsed time was 8 minutes, 8 seconds.

Means not taking into account sampling weights, even if specified

    Variable |    Obs        Mean    Std. Dev.       Min         Max
-------------+-----------------------------------------------------------
vulnerabil~y |  27252    19.71556    42.23636    -69.0705    311.0009
     poverty |  27252    10.79002    36.99031   -72.17365    222.8564
        risk |  27252    8.925538    10.83183    .3450165    214.5512
      agrisk |  27252    2.642975    3.897174    .0296936    54.46426
   idrisktot |  27252    .0973372    1.025253   -15.47354    22.57245
      idrisk1 |  27252      .00169    .1720691   -2.190704    3.632782
      idrisk2 |  27252    .0512714    .8611174   -14.09906    20.78229
      idrisk3 |  27252    .0443758    .6354942   -20.65897     10.8821
    unexprisk |  27252    6.185226    10.13041   -62.80118    206.4046

Bootstrapped confidence intervals for survey means of vulnerability measures.
These take into account sampling weights if specified.

Variable|Pop. Mean [ 90% Conf. Int.] [ 95% Conf. Int.] [ 99% Conf. Int.]
--------+----------------------------------------------------------------
vulnmean| 19.7156 [ 18.803, 20.342] [ 18.739, 20.603] [ 18.408, 20.668]
 povmean| 10.7900 [ 10.047, 11.266] [ 9.9456, 11.569] [ 9.7455, 11.671]
riskmean| 8.92554 [  8.487,  9.215] [ 8.4805, 9.3995] [ 8.2915, 9.5043]
agrism~n| 2.64297 [ 2.3832, 2.8239] [ 2.3665, 2.8743] [ 2.3312, 2.9335]
idrism~n| .097337 [ .04385, .14601] [ .04067, .14956] [ .02979, .16598]
idri1m~n|   .00169 [-.00555, .00865] [-.00606, .01175] [-.00808, .01495]
idri2m~n| .051271 [   .0076, .08856] [   .0062, .09177] [ .00139, .11755]
idri3m~n| .044376 [ .01263, .08196] [   .0096, .08907] [ .00336, .10299]
unexri~n| 6.18523 [ 5.8006, 6.5038] [ 5.7089, 6.5935] [  5.496, 6.6231]
```

```
Bootstrapped vulnerability regression
                                          No. of obs =    2271
                                          R-squared = .042026
-----------------------------------------------------------------------
Vuln~y| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+----------------------------------------------------------------
   sex|  8.647 [ 4.6015 , 11.963] [ 4.0608 , 13.036] [ 3.5984 , 14.232]
   age|-.18998 [-1.0932 , .67373] [-1.2776 , .74294] [-1.3566 , 1.0393]
  age2|-.00187 [-.00923 , .00607] [-.00999 , .00765] [-.01289 , .00796]
 educ2| -7.026 [-12.221 ,-1.7513] [-12.857 , .66348] [-16.634 , 1.6881]
 educ3|-18.659 [-25.971 ,-13.747] [-26.279 ,-11.930] [-26.550 ,-6.3839]
 educ4|-23.972 [-30.563 ,-17.611] [-31.833 ,-16.144] [-33.314 ,-11.714]
 res_~e| 6.3911 [ 1.8133 , 10.107] [ 1.7384 , 11.258] [-2.0808 , 11.878]
 anim~s|-7.3876 [-11.743 ,-4.2489] [-12.429 ,-3.4657] [-13.891 ,-2.4384]
 _cons| 41.882 [ 18.577 , 62.842] [ 17.463 , 68.165] [ 13.156 , 78.882]
-----------------------------------------------------------------------


Bootstrapped poverty regression
                                          No. of obs =    2271
                                          R-squared  = .04676
-----------------------------------------------------------------------
Pov~ty| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+----------------------------------------------------------------
   sex| 9.6916 [ 5.8943 , 12.968] [ 5.7189 , 13.283] [ 5.0213 , 14.724]
   age|-.09651 [-.72559 , .59829] [-.78668 , .71512] [-.93306 ,  1.081]
  age2|-.00205 [-.00824 , .00352] [-.00897 , .00468] [-.01264 , .00601]
 educ2| -7.416 [-12.511 ,-2.9839] [-12.826 ,-1.0922] [-16.666 , .98328]
 educ3|-17.113 [-23.380 ,-12.107] [-23.804 ,-10.690] [-24.309 ,-6.3424]
 educ4|-21.956 [-28.238 ,-16.645] [-29.451 ,-15.208] [-31.050 ,-10.992]
res_~e| 5.4515 [ 1.4525 , 8.9453] [ .80968 , 9.5435] [-1.7313 ,  9.807]
anim~s|-7.6892 [-11.701 , -4.755] [-12.685 ,-4.5431] [-12.828 ,-3.4933]
 _cons| 27.585 [ 9.0043 , 41.057] [ 8.2794 , 43.954] [ 1.2038 , 50.433]
-----------------------------------------------------------------------

Bootstrapped risk regression
                                          No. of obs =    2271
                                          R-squared  = .01177
-----------------------------------------------------------------------
  Risk| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+----------------------------------------------------------------
   sex|-1.0446 [-2.0929 ,-.10098] [-2.1952 , .07893] [ -2.706 , .59172]
   age|-.09347 [-.50212 , .13201] [-.58278 , .16401] [-.59877 , .22564]
  age2| .00018 [-.00174 , .00289] [-.00226 , .00424] [-.00246 , .00444]
 educ2|   .390 [-.63993 , 1.6436] [-1.0795 , 1.7557] [-1.6376 , 1.8926]
 educ3| -1.546 [-3.2116 ,-.04154] [-3.3765 , .42677] [-3.8464 , .94652]
 educ4|-2.0157 [-3.4692 ,-.54769] [-3.5682 ,-.15766] [-4.7864 , .31983]
res_~e|  .9396 [-.34948 , 1.9569] [-.57344 , 2.3126] [-1.0681 , 2.6388]
anim~s| .30165 [-.86645 , 1.2838] [ -1.063 , 1.4627] [-1.4347 ,  1.655]
 _cons| 14.297 [  7.621 , 22.804] [ 6.6435 , 27.272] [ 4.3171 , 28.570]
-----------------------------------------------------------------------
```

```
Bootstrapped aggregate risk regression
                                                No. of obs =    2271
                                                R-squared  = .031369
--------------------------------------------------------------------------
AggRis| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+-------------------------------------------------------------------
   sex| .13926 [-.26505 ,  .56966] [-.28886 ,  .65143] [-.37796 ,  .84462]
   age| .06617 [ .00995 ,  .13179] [  .0045 ,  .14426] [-.00684 ,  .16834]
  age2|-.00096 [-.00158 ,  -.0004] [-.00166 ,-.00035] [-.00196 ,-.00027]
 educ2|-.69793 [-1.4922 ,-.21102] [-1.5085 ,  .01802] [-2.1348 ,  .14736]
 educ3|-1.8118 [-2.5804 ,  -1.176] [-2.8313 ,-1.0513] [-3.2145 ,-.62184]
 educ4|-2.0665 [-2.8543 ,-1.4603] [-2.9803 ,-1.2956] [ -3.426 ,-1.0102]
res_~e| .36186 [-.12746 ,  .70131] [-.17023 ,  .91379] [-.38353 ,  1.0292]
anim~s|-.62415 [-1.0474 ,-.21611] [-1.1256 ,-.13437] [-1.3494 ,-.00588]
 _cons| 3.2829 [ 1.7193 ,  4.4783] [ 1.4375 ,  4.6397] [ 1.0797 ,  5.090]
--------------------------------------------------------------------------


Bootstrapped total idiosyncratic risk regression
                                                No. of obs =    2271
                                                R-squared  =  .00646
--------------------------------------------------------------------------
IdRisk| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+-------------------------------------------------------------------
   sex| .09222 [ .01227 ,  .18091] [  .0088 ,  .19702] [ .00483 ,  .22961]
   age| .01536 [-.00046 ,  .02934] [-.00067 ,  .03228] [-.00193 ,  .03654]
  age2|-.00013 [-.00027 , 1.9e-05] [-.00028 , 3.0e-05] [-.00033 , 3.8e-05]
 educ2| .04089 [-.11955 ,  .21751] [-.13585 ,  .27707] [-.19471 ,  .33734]
 educ3| .02923 [-.11829 ,   .2424] [ -.1556 ,  .27195] [-.19239 ,  .31715]
 educ4| .02716 [-.13678 ,  .22906] [-.20176 ,  .28546] [-.25854 ,  .34999]
res_~e| .10762 [-.01568 ,  .20938] [-.02218 ,  .21861] [-.05706 ,  .26965]
anim~s| -.0445 [-.16316 ,  .06909] [-.17048 ,  .10073] [-.19744 ,  .14509]
 _cons| -.4658 [-.76517 ,-.12544] [-.76978 ,-.09413] [-.93421 ,-.05621]
--------------------------------------------------------------------------


Bootstrapped idiosyncratic risk #1 regression
                                                No. of obs =    2271
                                                R-squared  = .008745
--------------------------------------------------------------------------
IdRis1| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+-------------------------------------------------------------------
   sex|-.00115 [-.01197 ,   .0106] [-.01772 ,  .01414] [-.01945 ,  .01597]
   age|-.00242 [-.00777 ,   .0019] [-.00854 ,  .00225] [-.01174 ,  .00694]
  age2| 2.8e-05[-8.6e-06,7.3e-05] [-1.6e-05,8.1e-05] [-5.6e-05,  .00011]
 educ2| .02999 [-.00029 ,  .06455] [-.00069 ,  .07477] [-.00202 ,  .10646]
 educ3| .04949 [ .01127 ,  .09013] [ .00785 ,  .10961] [-.00123 ,  .13881]
 educ4| .04771 [ .01296 ,  .08881] [ .00609 ,  .09695] [ .00421 ,  .14388]
res_~e| .01401 [-.00502 ,  .03241] [-.00818 ,  .04037] [-.02033 ,  .05317]
anim~s| .00803 [-.00596 ,  .02482] [-.00772 ,  .02825] [-.00891 ,  .04166]
 _cons|-.00303 [-.11781 ,  .13534] [-.12758 ,  .17171] [-.22838 ,  .21135]
--------------------------------------------------------------------------
```

```
Bootstrapped idiosyncratic risk #2 regression
                                        No. of obs =    2271
                                        R-squared  = .006364
-------------------------------------------------------------------------
IdRis2| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+------------------------------------------------------------------
   sex| .06192 [ -.0019 , .14119] [-.02154 , .17823] [-.02978 , .19256]
   age| .01149 [-.00224 , .02423] [-.00243 , .02911] [-.00453 , .03333]
  age2|-.00011 [-.00024 ,1.7e-05] [-.00028 ,3.2e-05] [-.00033 ,3.8e-05]
 educ2| .09494 [-.02769 , .26175] [-.03275 , .26991] [-.06839 , .29646]
 educ3|-.00741 [ -.1485 , .17644] [-.15917 , .19003] [-.21565 , .22905]
 educ4| .03478 [-.11206 , .22078] [-.15047 , .23377] [-.21061 ,  .2707]
res_~e| .02155 [-.12723 ,  .1172] [-.15089 , .13305] [-.27489 , .15302]
anim~s|-.08131 [-.21829 , .00905] [-.25731 , .04424] [-.36794 ,  .0652]
 _cons|-.27598 [-.51989 ,-.05265] [-.57568 ,-.00953] [-.58734 ,  .0648]
-------------------------------------------------------------------------


Bootstrapped idiosyncratic risk #3 regression
                                        No. of obs =    2271
                                        R-squared  = .005543
-------------------------------------------------------------------------
IdRis3| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+------------------------------------------------------------------
   sex| .03146 [ -.0218 , .09689] [-.02912 , .10594] [-.03938 , .11234]
   age| .00629 [-.00747 ,  .0167] [-.00843 , .02121] [-.01242 , .02202]
  age2|-4.8e-05[-.00018 ,7.6e-05] [-.00019 ,9.6e-05] [ -.0002 , .00012]
 educ2|-.08404 [-.17668 ,-.03892] [-.18149 ,-.03444] [-.23093 ,-.01364]
 educ3|-.01285 [-.08707 , .05125] [-.09122 , .06792] [-.15185 , .09411]
 educ4|-.05532 [-.14578 , .01557] [-.16226 , .04385] [-.17794 , .07623]
res_~e| .07207 [-.00739 ,   .260] [-.01168 , .28535] [-.03851 , .37629]
anim~s| .02878 [-.08745 , .23889] [-.08935 , .26957] [-.12044 , .36575]
 _cons|-.18679 [-.41347 , .01805] [-.48026 , .03905] [-.49991 , .12617]
-------------------------------------------------------------------------


Bootstrapped unexplained risk regression
                                        No. of obs =    2271
                                        R-squared  = .006784
-------------------------------------------------------------------------
UnxRis| Coef.   [ 90% Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]
------+------------------------------------------------------------------
   sex| -1.276 [-2.3256 ,-.49884] [-2.4212 ,-.39801] [-2.5913 , .13581]
   age|  -.175 [-.57067 , .03915] [-.60017 , .08155] [ -.6601 , .16678]
  age2| .00127 [-.00061 , .00344] [-.00087 , .00483] [-.00178 , .00521]
 educ2|  1.047 [ .00493 , 2.2815] [ -.4311 , 2.4152] [-.63311 , 2.7456]
 educ3| .23657 [-1.4021 , 1.7189] [-1.5456 , 2.2697] [-2.0024 , 2.5007]
 educ4| .02356 [ -1.615 , 1.7259] [-1.8966 , 1.8496] [-2.5229 , 2.5122]
res_~e| .47012 [-.64737 , 1.4604] [-.73571 , 1.8583] [-1.1727 , 2.0161]
anim~s| .97029 [ -.0577 , 1.9106] [-.22849 , 2.1914] [-.43945 , 2.4816]
 _cons| 11.479 [ 4.9616 , 20.981] [ 4.1902 , 23.484] [ 1.6111 , 25.386]
-------------------------------------------------------------------------

. drop poverty vulnerability *risk*;
. log close;
      log:  /home/schechte/bulgaria/vulnstata/sample.log
  log type: text
 closed on: 19 May 2003, 16:52:55
```

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vulncalc.ado

```
capture program drop vulncalc
program define vulncalc, eclass

  # delimit;
  version 7.0;
  ** THIS CODE PREDICTS CONSUMPTION BASED ON THE LINEAR CONSUMPTION
  ** PREDICTION EQUATION.;
  ** First we just get the syntax straight and name local macros.;
  ** i is household id variable
  ** t is time variable
  ** c is consumption variable (real per-capita)
  ** touse is 1 if vulnerability should be calculated for that household
    ** it is 1 iff, a)the household has an observation on consumption in
    ** each time period b) the household has positive consumption in every
    ** time period and c) the household was not `if'ed out in the user
    ** specified if command
  ** tousei is 1 if the household is not missing an observation in any time
    ** period on any of the idiosyncratic risk variables and if touse=1
    ** as well. If tousei is 0 idiosyncratic risk and unexplained risk will
    ** not be calculated for that household;
  ** ir`num' (i.e. ir1, ir2, ir3, etc.) are the idiosyncratic risk variables;
  ** `ir_n' is the number of idiosyncratic risk variables.;
  syntax varlist(min=5 default=none) [pweight] [, gamma(real 2) z(real 0)
    ir_n(integer 0) runreg (real 0) runregvar(varlist)];
  tokenize `varlist';
  local i `1';
  local t `2';
  local c `3';
  local touse `4';
  local tousei `5';
  macro shift 5;
  forvalues num= 1/`ir_n' {;
    local ir`num' ``num'';
  };
  macro shift `ir_n';
  tokenize `exp';
  local w `2';
  if "`w'"=="" {;
    tempvar w;
    quietly gen `w'=1;
  };

  ** The user specifies the value of z in the ,z(#) option.
  ** The default is 0.
  ** If z=0 we normalize consumption, dividing by average
  ** (over time periods and over households) consumption.;
  ** Thus the average of normalized consumption, EEC, will be 1.
  ** The reference consumption, Ref, will also be 1.
  ** If z~=0 we normalize consumption, dividing by the poverty line.;
  ** In this case the average of normalized consumption, EEC, will be
  ** the average consumption divided by the poverty line,
  ** Reference consumption, Ref, will be the poverty line divided by the
  ** poverty line, so it will still be 1.
  ** c1 is our new normalized consumption.
  ** Ref is the reference consumption used in the calculation.
```

```
** If all households had normalized consumption= Ref there would be no
** poverty, no risk, and no vulnerability in the population.;
tempvar c1 EEC;
tempname e;
sort `touse';
if `z'==0 {;
  quietly by `touse': gen `EEC'=sum(`c'*`w')/sum(`w') if `touse'==1;
  quietly by `touse': replace `EEC'=`EEC'[_N] if `touse'==1;
  quietly generate `c1'=`c'/`EEC' if `touse'==1;
  local ref=1;
  quietly replace `EEC'=1;
};
else if `z'>0 {;
  quietly generate `c1'=`c'/`z' if `touse'==1;
  quietly by `touse': gen `EEC'=sum(`c1'*`w')/sum(`w') if `touse'==1;
  quietly by `touse': replace `EEC'=`EEC'[_N] if `touse'==1;
  local ref=1;
};


** Now we predict each households expected consumption linearly
** as the households average consumption.
** The prediction will be EC.;
** CCh will be EC minus the reference consumption (EEC)
** i.e. the mean-0 household effect.;
tempvar EC CCh;
quietly egen `EC'= mean(`c1') if `touse'==1, by(`i');
quietly gen `CCh'=`EC'-`EEC';


** Next we want to make the predictions of consumption based on
** aggregate shocks. We do that by calculating average consumption
** in each month, minus overall average consumtion.
** ET is average consumption by month.
** CCt is average consumption by month minus overall average consumption,
** i.e. the mean-0 time period effect.;
tempvar CCt ET;
sort `touse' `t';
quietly by `touse' `t': gen `ET' = sum(`c1'*`w')/sum(`w') if `touse'==1;
quietly by `touse' `t': replace `ET'=`ET'[_N] if `touse'==1;
quietly gen `CCt'=`ET' - `EEC';


** Now we will orthogonalize each idiosyncratic risk variable
  ** (minus its time mean and minus its household mean
  ** and plus its overall mean).
** We first take out the time and houshold means and add
  ** in the overall mean to each idiosyncratic risk variable.;
** ir`num' are the original idiosyncratic risk variables.;
** irnew`num' will be the new mean-0 idiosyncratic risk variables.;
forvalues num= 1/`ir_n' {;
  sort `tousei' `t';
  tempvar irnew`num' r`num' ECgI`num' mean`num' j`num' t`num';
  quietly gen `irnew`num''=`ir`num'' if `tousei'==1;
  quietly by `tousei': gen `mean`num'' = sum(`irnew`num''*`w') / sum(`w')
    if `tousei'==1;
  quietly by `tousei': replace `mean`num''=`mean`num''[_N] if `tousei'==1;
  quietly egen `j`num''=mean(`irnew`num'') if `tousei'==1,
```

```
     by (`i');
   quietly by `tousei' `t': gen `t`num''=sum(`irnew`num''*`w') / sum(`w')
      if `tousei'==1;
   quietly by `tousei' `t': replace `t`num''=`t`num''[_N] if `tousei'==1;
   quietly replace `irnew`num''=`irnew`num''-`j`num''
      -`t`num'' +`mean`num'' if `tousei'==1;

** Now we do the orthogonalization.
** We do this by regressing the id risk var #2 on idrisk var #1,
   ** save resid r2;
** Then we regress id risk var #3 on idrisk var #2 and idriskvar #1,
   ** save resid r3;
** and we go on like this until we have completed it
** for all the idiosyncratic risk variables.;
forvalues num= 2/`ir_n' {;
   local it1=`num'-1;
   quietly reg `irnew`num'' `irnew1'-`irnew`it1'' [`weight' `exp'];
   quietly predict `r`num'', resid;

** Now comes the prediction equation:
** We regress Y =hh cons minus overall ave cons on
   ** A) time mean of cons - overall mean
   ** B) hh mean of cons - overall mean
   ** C) decomposed orthogonal version of idiosyncratic risk variables.;
** and save the resulting coefficients.;
tempvar Y;
tempname Beta ;
quietly gen `Y'=`c1'-`EEC';
if `ir_n'==1 {;
   quietly reg `Y' `CCh' `CCt' `irnew1' [`weight' `exp'];
   matrix `Beta'= e(b);
};
else if `ir_n'>1 {;
   quietly reg `Y' `CCh' `CCt' `irnew1' `r2'- `r`ir_n'' [`weight' `exp'];
   matrix `Beta'= e(b);
};
** We save coefficients BetaA BetaB BetaC1 BetaC2 etc. from this regression
** Note that BetaA and BetaB will be equal to 1 because they are the
** fixed time and household effects;

** Third, we calculate expected consumptions based on each of these things
** one at a time.
** So, Exp. Cons.  given hh fixed effect is:
   ** ave cons + BetaA*CCh
** Exp Cons given hh fixed effect and time effect
   ** ave cons + BetaA*CCh + BetaB*CCt
** (Note that everything up to here we can do for households with missing
   **data for some idiosyncratic risk variable. The next part will no longer
   **include them.)
** Exp Cons given hh effect, time effect, and first idiosyncratic risk effect
   ** ave cons + BetaA*CCh + BetaB*CCt + (decomposedC1 * BetaC1)
** etc. etc.;
** The variables are ECgH--expected consumption given household mean.
** ECgT--expected consumption given household and time mean.
** ECgI1--expected consumption given household and time mean and
** first idiosyncratic risk variable. etc. etc.;
tempvar ECgH ECgT;
quietly generate `ECgH'=`EEC'+`CCh';
```

```
quietly generate `ECgT'=`ECgH'+`CCt';
forvalues num= 1/`ir_n' {;
if `num'==1 {;
quietly generate `ECgI1'=`ECgT'+`Beta'[1,3]*`irnew1';
else if `num' ~=1 {;
local it1=`num'-1;
quietly generate `ECgI`num''=`ECgI`it1'' +
`Beta'[1,`num'+2]*`r`num'';

  ** This calls on vulncalc2, which is the code that takes the consumption
  ** predictions and calculates vulnerability, poverty, and risk measures.;
  if `runreg'==0 {;
    if `ir_n'>0 {;
      vulncalc2 `i' `t' `c1' `touse' `tousei' `ECgH' `ECgT'
        `ECgI1'-`ECgI`ir_n'' [`weight' `exp'], gamma(`gamma')
        ir_n(`ir_n') ref(`ref');
    };
    else if `ir_n'==0 {;
      vulncalc2 `i' `t' `c1' `touse' `tousei' `ECgH' `ECgT'
        [`weight' `exp'], gamma(`gamma') ir_n(`ir_n') ref(`ref');
    };
  };
  else if `runreg'==1 {;
    if `ir_n'>0 {;
      vulncalc2 `i' `t' `c1' `touse' `tousei' `ECgH' `ECgT'
        `ECgI1'-`ECgI`ir_n'' [`weight' `exp'], gamma(`gamma') ir_n(`ir_n')
        runreg (1) runregvar(`runregvar') ref(`ref');
    };
    else if `ir_n'==0 {;
      vulncalc2 `i' `t' `c1' `touse' `tousei' `ECgH' `ECgT'
        [`weight' `exp'], gamma(`gamma') ir_n(`ir_n')
runreg (1) runregvar(`runregvar') ref(`ref');
end;
```

vulncalc2.ado

```
capture program drop vulncalc2
program define vulncalc2, eclass

  # delimit;
  version 7.0;
  ** VULNCALC2 USES THE CONSUMPTION PREDICTIONS FROM VULNCALC
  ** TO CALCULATE VULNERABILITY, POVERTY, AND RISK VARIABLES.
  ** First we just get the syntax straight and name local macros.;
  ** i is household id variable
  ** t is time variable
  ** c1 is normalized consumption variable (real per-capita)
  ** touse is 1 if vulnerability should be calculated for that household
    ** it is 1 iff, a)the household has an observation on consumption in
    ** each time period b) the household has positive consumption in every
    ** time period and c) the household was not `if'ed out in the user
    ** specified if command
  ** tousei is 1 if the household is not missing an observation in any time
    ** period on any of the idiosyncratic risk variables and if touse=1
    ** as well. If tousei is 0 idiosyncratic risk and unexplained risk will
    ** not be calculated for that household;
  ** ECgH is predicted consumption based on hh identity.
  ** ECgT is predicted consumption based on hh identity and aggregate shocks.
  ** ECg1-N are predicted consumptions based on hh identity, aggregate
    ** shocks, and each previous idiosyncratic risk variable.
  ** `ir_n' is the number of idiosyncratic risk variables.;
  ** `ref' is reference utility, (i.e. 1).;
  syntax varlist(min=7 default=none) [pweight] [, gamma(real 2)
    ir_n(integer 0) runreg(real 0) runregvar(varlist) ref(real 1)];
  tokenize `varlist';
  local i `1';
  local t `2';
  local c1 `3';
  local touse `4';
  local tousei `5';
  local ECgH `6';
  local ECgT `7';
  macro shift 7;
  forvalues num= 1/`ir_n' {;
    local ECgI`num' ``num'';
    tempvar UECgI`num' EUECgI`num';
    global i`num' "idrisk`num'";
  };

****THE SECOND HALF OF THE CODE USES THE CONSUMPTION PREDICTIONS**********;
****ESTIMATED IN THE FIRST HALF OF THE CODE*****************************;
****TO CALCULATE THE VULNERABILITY MEASURES*****************************;

  ** We can now start estimating vulnerability over the relevant households.
  ** We will now calculate (Uref), which is either utility from the
  ** reference consumption. Uref =U(ref);
  ** You will note that we multiply all utilities by 100.
  ** Because of that, when gamma=2, we can interpret vulnerability as
  ** the percent utility loss due to vulnerability.;
  tempname Uref;
  if `gamma'~=1 {;
    scalar `Uref'=100*(`ref'^(1-`gamma'))/(1-`gamma');
```

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```
};
else if `gamma'==1 {;
  scalar `Uref'=100*ln(`ref');
};


** We will now calculate expected utility (EUC) for each household.;
** This is the average of their actual utilities (UC) in each time period.;
tempvar UC EUC;
if `gamma'==1 {;
  quietly generate `UC'=100*ln(`c1');
  quietly egen `EUC'= mean(`UC') if `touse'==1, by(`i');
};
else if `gamma' ~=1 {;
  quietly generate `UC'=100*(`c1'^(1-`gamma'))/(1-`gamma');
  quietly egen `EUC'=mean(`UC') if `touse'==1, by(`i');
** Ligon-Schechter define vulnerability as [(Uref-UEC)+(UEC-EUC)].;
** Where the first part is poverty and the second is risk.;
** We can now calculate vulnerability.;
global v "vulnerability";
quietly gen $v = `Uref'-`EUC';


** Now we will calculate poverty, risk, aggregate risk, idiosyncratic
** risk, and unexplained risk.;
** To do so we calculate utility of predicted consumption given
** each new piece of information.;
tempvar UECgH UECgT;
if `gamma'==1 {;
  quietly gen `UECgH'=100*ln(`ECgH');
  quietly gen `UECgT'=100*ln(`ECgT');
  forvalues num= 1/`ir_n' {;
    quietly gen `UECgI`num''=100*ln(`ECgI`num'');
if `gamma'~=1 {;
  quietly gen `UECgH'=100*(`ECgH'^(1-`gamma'))/(1-`gamma');
  quietly gen `UECgT'=100*(`ECgT'^(1-`gamma'))/(1-`gamma');
  forvalues num= 1/`ir_n' {;
    quietly gen `UECgI`num''=100*(`ECgI`num''^(1-`gamma'))/(1-`gamma');
  };
};


** Then we calculate expected utility of predicted consumption
** given each new piece of information.;
tempvar EUECgH EUECgT;
quietly egen `EUECgH'=mean(`UECgH') if `touse'==1, by(`i');
quietly egen `EUECgT'=mean(`UECgT') if `touse'==1, by(`i');
forvalues num= 1/`ir_n' {;
  quietly egen `EUECgI`num''=mean(`UECgI`num'') if `touse'==1, by(`i');
};


** Then we calculate each component of risk
** by calculating the difference of expected utilities
** given each new piece of information.;
global p "poverty";
global r "risk";
global a "agrisk";
global u "unexprisk";
quietly gen $p = `Uref'-`EUECgH';
quietly gen $r = `EUECgH' - `EUC';
quietly gen $a=`EUECgH'-`EUECgT';
```

```
if `ir_n'>0 {;
  quietly gen $i1=`EUECgT'-`EUECgI1';
  if `ir_n'>1{;
    local it1=1;
    forvalues num= 2/`ir_n' {;
      quietly gen ${i`num'}=`EUECgI`it1''-`EUECgI`num'';
      local it1=`it1'+1;
    };
  };
  quietly gen $u=`EUECgI`ir_n''-`EUC';
};
else if `ir_n'==0 {;
  quietly gen $u=`EUECgT'-`EUC';
};
global it "idrisktot";
if `ir_n'>0 {;
  quietly egen $it=rsum($i1-${i`ir_n'}) if `tousei'==1;
};
else if `ir_n'==0 {;
   quietly gen $it=0 if `touse'==1;
};

** This part will run the regression if the user requests to do so.
** Remember that there will only be one observation for each household.
** Thus, the average of any time-varying variable will be used
** on the left hand side.;
if `runreg'==1 {;
  local iterate=0;
  global runregBetav "runregBetav";
  global runregBetap "runregBetap";
  global runregBetar "runregBetar";
  global runregBetaa "runregBetaa";
  global runregBetait "runregBetait";
  global runregBetau "runregBetau";
  global r2v "r2v";
  global r2p "r2p";
  global r2r "r2r";
  global r2a "r2a";
  global r2it "r2it";
  global r2u "r2u";
  global Nv "Nv";
  global Ni "Ni";
  foreach var of varlist `runregvar' {;
    local iterate=`iterate'+1;
    global namerrv`iterate' "`var'";
    tempvar runregvar`iterate';
    quietly egen `runregvar`iterate''=mean(`var') if `touse'==1, by(`i');
  };
  quietly reg $v `runregvar1'-`runregvar`iterate'' if `t'==1
    [`weight'`exp'];
  matrix $runregBetav=e(b);
  scalar $r2v=e(r2);
  scalar $Nv=e(N);
  quietly reg $p `runregvar1'-`runregvar`iterate'' if `t'==1
    [`weight'`exp'];
  matrix $runregBetap=e(b);
  scalar $r2p=e(r2);
  quietly reg $r `runregvar1'-`runregvar`iterate'' if `t'==1
```

```
        [`weight'`exp'];
      matrix $runregBetar=e(b);
      scalar $r2r=e(r2);
      quietly reg $a `runregvar1'-`runregvar`iterate'' if `t'==1
        [`weight'`exp'];
      matrix $runregBetaa=e(b);
      scalar $r2a=e(r2);
      quietly reg $it `runregvar1'-`runregvar`iterate'' if `t'==1
        [`weight'`exp'];
      matrix $runregBetait=e(b);
      scalar $r2it=e(r2);
      quietly reg $u `runregvar1'-`runregvar`iterate'' if `t'==1
        [`weight'`exp'];
      matrix $runregBetau=e(b);
      scalar $r2u=e(r2);
      forvalues num= 1/`ir_n' {;
        global runregBetai`num' "runregBetai`num'";
        global r2i`num' "r2i`num'";
        quietly reg ${i`num'} `runregvar1'-`runregvar`iterate'' if `t'==1
          [`weight'`exp'];
        matrix ${runregBetai`num'}=e(b);
        scalar ${r2i`num'}=e(r2);
      };
      scalar $Ni=e(N);
    };
end;
```

vulnerability.ado

```
capture program drop vulnerability
program define vulnerability, eclass sortpreserve

  # delimit;
  version 7.0;
  ** The panel data should be in `long' form (see help reshape);
  ** This code will work with an unbalanced panel,;
  ** but will ignore those households with missing consumption variables.;
  ** It will also ignore households with negative or zero consumption;
  ** in any period.;
  ** You are allowed any # of variables which represent idosyncratic risk.
  ** These variables must vary over time, and if you are including
  ** a variable such as income it should be in real per capita terms already.;
  ** If there is a household with missing data for the idiosyncratic risk
  ** variable, it will be excluded from the calculation of idiosyncratic
  ** and unexplained risk, but will still be included in the calculation
  ** of vulnerability, poverty, risk, and aggregate risk.
  ** Please note that this code creates variables called vulnerability,;
  ** poverty, risk, agrisk, idrisktot, unexprisk and idrisk1-N.;
  ** If you already have a variable with one of those names;
  ** the program will say, e.g. "vulnerability already defined";
  ** If you would like to calculate vulnerability twice, for example;
  ** once using total consumption and once using food consumption,;
  ** You should run it the first time and then rename the output variables;
  ** before running it again.;

  syntax varlist(min=3 default=none) [pweight] [if]
   [, gamma(real 2) z(real 0) boot(integer 0)
   nreps(integer 1000) runregvar(varlist)];
  tokenize `varlist';
  local i `1';
  local t `2';
  local c `3';
  macro shift 3;
  local  ir `*';
  tokenize `exp';
  local w `2';
  if "`w'"=="" {;
    tempvar w;
    quietly gen `w'=1;
  };

  ** The arguments for this function are, in that order,
  ** i (household id variable name) t (time period variable name)
  ** c (consumption variable name), followed by ir (any idiosyncratic
  ** risk variables).
  ** Gamma (the constant of relative risk aversion)
  ** and z(whether vulnerability will be calculated with respect to
  ** a poverty line, or with respect to average consumption) are also inputs.
  ** Consumption and income variables must be in real per-capita terms.
  ** The default for gamma is 2,
  ** but real numbers greater than or equal to 1 are permitted.
  ** For gamma=1 the utility function is log utility.
  ** For gamma>1 the utility function is CRS with CRRA of gamma.
  ** For z=0 average consumption is used as the reference point.
  ** Thus relative vulnerability is calculated.
```

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```
** For z~=0, z is the poverty line.
** The default for z is 0.
** pweights are allowed, w is the sampling weight.
** For boot=1, a bootstrap will be done, for boot=0 it will not.
** The default is boot=0.
** nreps is the number of repetitions for a bootstrap.
** The default is nreps=1000.
** If runregvar is specified a regression will be run and
** the variables in runregvar will be the RHS variables.;

** This part will make sure that the numbers input by the user
** are appropriate.;
if `gamma'<1 {;
  display as error "The constant of relative risk aversion" _continue;
  display " must be at least 1 or higher.";
  error 459;
};
if `z'<0 {;
  display as error "z must be either 0 or positive.";
  error 459;
};
if `nreps'<=0 {;
  display as error "The number of repetitions must be" _continue;
  display " an integer greater than 0.";
  error 459;
};
if `boot'~=0 & `boot'~=1 {;
  display as error "boot must be 0 or 1";
  error 459;
};
if "`runregvar'"~="" {;
  local runreg=1;
};
else if "`runregvar'"=="" {;
  local runreg=0;
};

** This part of the code will find those households with negative
** consumption in any period and those with missing variables;
** It does so by temporarily converting the data to wide format
** and finding the observations with missing variables.;
** `missingc' are those households with missing consumption data.
** `missingi' are those households without missing id. risk data.
** `negg' are those households with negative cons. in some period.
** `useriff' are those households specified to be used by the user
  ** in his or her if command.;
** The part with `userif' and `useriff' gets a bit complicated because
** it will not only allow the user to specify a prerequesite such as
** "if age<50" (the `useriff' part of the commands). It will also allow
** the user to specify a prerequesite such as "if month~=12"
** (which gives the `userif' parts of the commands).;
tempname N;
tempvar neg negg userif useriff fake_t missingc missingi;
quietly egen `fake_t'=group(`t') `if';
quietly summ `fake_t';
local fake_t_max=r(max);
gen `neg'=0;
gen `userif'=0;
```

```
quietly replace `userif'=1 `if';
egen `useriff'=sum(`userif'), by(`i');
quietly replace `neg'=1 if `c' <=0 & `useriff'==`fake_t_max';
egen `negg' =sum(`neg'), by(`i');
preserve;
drop `fake_t';
quietly egen `fake_t'=group(`t');
keep `c' `i' `fake_t' `ir';
quietly reshape wide `c' `ir', i(`i') j(`fake_t');
gen `missingc'=0;
gen `missingi'=0;
forvalues num= 1/`fake_t_max' {;
  quietly replace `missingc' =1 if `c'`num'==.;
  foreach var in `ir' {;
    quietly replace `missingi'=1 if `var'`num'==.;
  };
};
keep `i' `missingc' `missingi';
sort `i';
quietly summ `i';
scalar `N'=r(N);
tempfile file1;
quietly save `file1';
restore;
sort `i';
merge `i' using `file1';
drop _merge;

** This marks out those households with negative consumption
** or unbalanced data over the relevant variable set;
** It then informs the user how many observations will be ignored.;
** For hh's with touse=1, vuln, pov, and agg risk will be calculated.;
** For hh's with tousei=1 as well, idiosyncratic and unexplained risk will
** be calculated as well.;
tempvar touse tousei;
gen `touse'=(`negg'==0 & `missingc'==0);
tempvar touse_hh;
tempname k_touse;
egen `touse_hh'=sum(`touse'), by(`t');
quietly summ `touse_hh';
scalar `k_touse'=r(min);
scalar `k_touse'=`N'-`k_touse';
display "";
if `k_touse'>0 {;
  display "";
  display as text "We will ignore the " _continue;
  display as error `k_touse' as text " households" _continue;
  display " with negative or 0 consumption or";
  display "missing data for consumption in at least one time period.";
};
else {;
  display "";
  display as text "We will calculate a vulnerability measure for";
  display "every household, as it is a balanced panel";
  display "and there are no observations with negative consumption.";
};
quietly replace `touse'=(`negg'==0 & `missingc'==0
  & `useriff'==`fake_t_max' & `userif'==1);
```

```
quietly gen `tousei'=(`missingi'==0 & `touse'==1);

** Here we count how many idiosyncratic risk variables (ir) were entered.;
local iterate=0;
if "`ir'"~="" {;
  foreach var of varlist `ir' {;
    local iterate=`iterate'+1;
    tempvar ee`iterate';
    tempname im`iterate';
  };
};
local ir_n=`iterate';

** We will now run the bootstrap if that was requested.;
if `boot'==1 {;
  ** Here we are opening the postfiles to post the bootstrap results to.;
  tempname vm;
  tempfile bootstrap;
  postfile `vm' vulnmean povmean riskmean agriskmean idrisktotmean
    unexpriskmean using `bootstrap';
  forvalues num= 1/`ir_n' {;
    tempfile bootstrap`num';
    postfile `im`num'' idrisk`num'mean using `bootstrap`num'';
  };
  if `runreg'==1 {;
    local iterate=0;
    foreach var of varlist `runregvar' {;
      local iterate=`iterate'+1;
      tempfile regboot`iterate';
      tempname rrvbeta`iterate';
      postfile `rrvbeta`iterate'' rrbeta`iterate'v rrbeta`iterate'p
        rrbeta`iterate'r rrbeta`iterate'a rrbeta`iterate'it
        rrbeta`iterate'u using `regboot`iterate'';
      forvalues num= 1/`ir_n' {;
        tempfile regboot`iterate'i`num';
        tempname rrvbeta`iterate'i`num';
        postfile `rrvbeta`iterate'i`num'' rrbeta`iterate'i`num'
          using `regboot`iterate'i`num'';
      };
    };
    tempname rrvbetaconst;
    tempfile regbootconst;
    postfile `rrvbetaconst' rrbetaconstv rrbetaconstp rrbetaconstr
      rrbetaconsta rrbetaconstit rrbetaconstu using `regbootconst';
    forvalues num= 1/`ir_n' {;
      tempname rrvbetaconsti`num';
      tempfile regbootconsti`num';
      postfile `rrvbetaconsti`num'' rrbetaconsti`num'
        using `regbootconsti`num'';
    };
  };

  local st="$S_TIME";
  ** Here we actually run the bootstrap. The computer will count out
  ** every 50 repetitions as well as displaying the elapsed time
  ** between (st) over each 50 repetitions.;
  tempvar aa bb cc dd ee ff;
  display as text "";
```

```
display "The computer will count out every 50 repetitions...";
preserve;
forvalues num= 1/`nreps' {;
  local in=`num'/50;
  local inl1=inlist(`in',1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,
    19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,
    41,42,43,44,45,46,47,48,49,50,61,62,63,64,65,66,67,68,69,70,71,72,
    73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94);
  local inl2=inlist(`in',95,96,97,98,99,100,101,102,103,104,105,106,
    107,108,109,110,111,112, 113,114,115,116,117,118,119,120,121,122,123,
    124,125,126,127,128,129,130,131,132,133,134,135,136,137,138,139,140,
    141,142,143,144,145,146,147,148,149,150,151,152,153,154,155,156,157);
  local inl3=inlist(`in',158,159,160,161,162,163,164,165,166,167,168,169,
    170,171,172,173,174,175,176,177,178,179,180,181,182,183,184,185,186,
    187,188,189,190,191,192,193,194,195,196,197,198,199,200);
  if `inl1'==1 | `inl2'==1 |`inl3'==1 {;
    display "Repetition #" `num';
  elapse `st'; local st="$S_TIME";
  };
  quietly drop if `touse'==0;
  bsample, cluster(`i');
  if `runreg'==0 {;
    vulncalc `i' `fake_t' `c' `touse' `tousei' `ir' [`weight' `exp'],
      gamma(`gamma') z(`z') ir_n(`ir_n') runreg(0);
  };
  else if `runreg'==1 {;
    vulncalc `i' `fake_t' `c' `touse' `tousei' `ir' [`weight' `exp'],
      gamma(`gamma') z(`z') ir_n(`ir_n') runreg(1) runregvar(`runregvar');
  };
  ** This part calculates the average vulnerability measures
  ** in the bootstrapped sample, and the beta coefficients given
  ** by the bootstrapped sample and posts them to the postfile.;
  sort `tousei';
  quietly gen `aa' = sum($v*`w')/sum(`w') if $v~=.;
  local aaa=`aa'[_N];
  quietly gen `bb' = sum($p*`w')/sum(`w') if $p~=.;
  local bbb=`bb'[_N];
  quietly gen `cc' = sum($r*`w')/sum(`w') if $r~=.;
  local ccc=`cc'[_N];
  quietly gen `dd' = sum($a*`w')/sum(`w') if $a~=.;
  local ddd=`dd'[_N];
  quietly gen `ee' = sum($it*`w')/sum(`w') if $it~=.;
  local eee=`ee'[_N];
  quietly gen `ff' = sum($u*`w')/sum(`w') if $u~=.;
  local fff=`ff'[_N];
  post `vm' (`aaa') (`bbb') (`ccc') (`ddd') (`eee') (`fff');
  forvalues num2= 1/`ir_n' {;
    tempvar `ee`num2'';
    quietly gen `ee`num2'' = sum(${i`num2'}*`w')/sum(`w') if ${i`num2'}~=.;
    local eee`num2'=`ee`num2''[_N];
    post `im`num2'' (`eee`num2'');
    drop ${i`num2'};
  };
  if `runreg'==1 {;
    local rrv_n=colsof($runregBetav)-1;
    forvalues num2=1/`rrv_n' {;
      tempname rrb`num2'v rrb`num2'p rrb`num2'r rrb`num2'a rrb`num2'it
        rrb`num2'u;
```

```
        scalar `rrb`num2'v' = el($runregBetav,1,`num2');
        scalar `rrb`num2'p' = el($runregBetap,1,`num2');
        scalar `rrb`num2'r' = el($runregBetar,1,`num2');
        scalar `rrb`num2'a' = el($runregBetaa,1,`num2');
        scalar `rrb`num2'it' = el($runregBetait,1,`num2');
        scalar `rrb`num2'u' = el($runregBetau,1,`num2');
        post `rrvbeta`num2'' (`rrb`num2'v') (`rrb`num2'p') (`rrb`num2'r')
          (`rrb`num2'a') (`rrb`num2'it') (`rrb`num2'u');
        scalar drop `rrb`num2'v' `rrb`num2'p' `rrb`num2'r' `rrb`num2'a'
          `rrb`num2'it' `rrb`num2'u';
        forvalues num3= 1/`ir_n' {;
          tempname rrb`num2'i`num3';
          scalar `rrb`num2'i`num3'' = el(${runregBetai`num3'}, 1, `num2');
          post `rrvbeta`num2'i`num3'' (`rrb`num2'i`num3'');
          scalar drop `rrb`num2'i`num3'';
        };
      };
      tempname rrbconstv rrbconstp rrbconstr rrbconsta rrbconstit rrbconstu;
      scalar `rrbconstv'=el($runregBetav,1,`rrv_n'+1);
      scalar `rrbconstp'=el($runregBetap,1,`rrv_n'+1);
      scalar `rrbconstr'=el($runregBetar,1,`rrv_n'+1);
      scalar `rrbconsta'=el($runregBetaa,1,`rrv_n'+1);
      scalar `rrbconstit'=el($runregBetait,1,`rrv_n'+1);
      scalar `rrbconstu'=el($runregBetau,1,`rrv_n'+1);
      post `rrvbetaconst' (`rrbconstv') (`rrbconstp') (`rrbconstr')
        (`rrbconsta') (`rrbconstit') (`rrbconstu') ;
      forvalues num3= 1/`ir_n' {;
        tempname rrbconsti`num3';
        scalar `rrbconsti`num3''=el(${runregBetai`num3'},1,`rrv_n'+1);
        post `rrvbetaconsti`num3'' (`rrbconsti`num3'');
        scalar drop `rrbconsti`num3'';
        matrix drop ${runregBetai`num3'};
      };
      matrix drop $runregBetav $runregBetap $runregBetar $runregBetaa
        $runregBetait $runregBetau;
      scalar drop `rrbconstv' `rrbconstp' `rrbconstr' `rrbconsta'
        `rrbconstit' `rrbconstu' `num3';
    };
    drop $v $p $r $a $it $u  `aa' `bb' `cc' `dd' `ee' `ff';
    restore, preserve;
  };
  restore, not;

  ** And then we close the postfiles.;
  postclose `vm';
  forvalues num= 1/`ir_n' {;
    postclose `im`num'';
  };
  if `runreg'==1 {;
    forvalues num= 1/`rrv_n' {;
      postclose `rrvbeta`num'';
      forvalues num2=1/`ir_n' {;
        postclose `rrvbeta`num'i`num2'';
      };
    };
    postclose `rrvbetaconst';
    forvalues num2=1/`ir_n' {;
      postclose `rrvbetaconsti`num2'';
```

```
      };
    };
  };


  ** We will now call up the program which actually estimates vulnerability
  ** on the true sample.;
  preserve;
  tempfile newvars;
  if `runreg'==0 {;
    vulncalc `i' `fake_t' `c' `touse' `tousei' `ir' [`weight' `exp'],
      gamma(`gamma') z(`z') ir_n(`ir_n') runreg(0);
  };
  else if `runreg'==1 {;
    vulncalc `i' `fake_t' `c' `touse' `tousei' `ir' [`weight' `exp'],
      gamma(`gamma') z(`z') ir_n(`ir_n') runreg(1) runregvar(`runregvar');
  };
  if `ir_n'>0 {;
    keep `i' $v $p $r $a $it $i1-${i`ir_n'} $u;
  };
  else if `ir_n'==0 {;
    keep `i' $v $p $r $a $it $u;
  };
  sort `i';
  quietly save `newvars';
  restore;
  sort `i';
  merge `i' using `newvars';
  drop _merge;


  display "";
  display "";
  display as text "Means not taking into account sampling weights, even if
specified";
  if `ir_n'>0 {;
    summ $v $p $r $a $it $i1-${i`ir_n'} $u;
  };
  else if `ir_n'==0 {;
    summ $v $p $r $a $it $u;
  };
  preserve;

  ** And all the rest of the code is used to display the results nicely
  ** and has no economic content.;
  if `boot'==1 {;
    sort `tousei';
    tempvar realv realp realr reala realit realu;
    quietly gen `realv' = sum($v*`w')/sum(`w') if $v~=.;
    local realvv=`realv'[_N];
    quietly gen `realp' = sum($p*`w')/sum(`w') if $p~=.;
    local realpp=`realp'[_N];
    quietly gen `realr' = sum($r*`w')/sum(`w') if $r~=.;
    local realrr=`realr'[_N];
    quietly gen `reala' = sum($a*`w')/sum(`w') if $a~=.;
    local realaa=`reala'[_N];
    quietly gen `realit' = sum($it*`w')/sum(`w') if $it~=.;
    local realitt=`realit'[_N];
```

```
    quietly gen `realu' = sum($u*`w')/sum(`w') if $u~=.;
    local realuu=`realu'[_N];
    forvalues num= 1/`ir_n' {;
      tempvar reali`num';
      quietly gen `reali`num'' = sum(${i`num'}*`w')/sum(`w') if ${i`num'}~=.;
      local realii`num'=`reali`num''[_N];
    };
  };
  if `runreg'==1 {;
    local rrv_n=colsof($runregBetav)-1;
    forvalues num= 1/`rrv_n' {;
      local realb`num'v=el($runregBetav,1,`num');
      local realb`num'p=el($runregBetap,1,`num');
      local realb`num'r=el($runregBetar,1,`num');
      local realb`num'a=el($runregBetaa,1,`num');
      local realb`num'it=el($runregBetait,1,`num');
      local realb`num'u=el($runregBetau,1,`num');
      forvalues num2=1/`ir_n' {;
        local realb`num'i`num2'=el(${runregBetai`num2'},1, `num');
      };
    };
    local num=`rrv_n'+1;
    local realbconstv=el($runregBetav,1,`num');
    local realbconstp=el($runregBetap,1,`num');
    local realbconstr=el($runregBetar,1,`num');
    local realbconsta=el($runregBetaa,1,`num');
    local realbconstit=el($runregBetait,1,`num');
    local realbconstu=el($runregBetau,1,`num');
    forvalues num2= 1/`ir_n' {;
      local realbconsti`num2'=el(${runregBetai`num2'},1,`num');
    };
  };

  if `boot'==1 {;
    if `runreg'==1 {;
      local Nv=$Nv;
      local Ni=$Ni;
      local r2v=$r2v;
      local r2p=$r2p;
      local r2r=$r2r;
      local r2a=$r2a;
      local r2it=$r2it;
      local r2u=$r2u;
      forvalues num=1/`ir_n'{;
        local r2i`num'=${r2i`num'};
      };
    };
    clear;
    quietly use `bootstrap';
    forvalues num= 1/`ir_n' {;
      merge using `bootstrap`num'';
      drop _merge;
    };
    sort vulnmean;
    gen id=_n;
    tempname n_1l n_1h n_5l n_5h n_10l n_10h;
    quietly summ id;
    local n_max=r(max);
```

```
scalar `n_1l'=round((.005*`n_max'),1);
scalar `n_1h'=round((.995*`n_max'),1);
scalar `n_5l'=round((.025*`n_max'),1);
scalar `n_5h'=round((.975*`n_max'),1);
scalar `n_10l'=round((.05*`n_max'),1);
scalar `n_10h'=round((.95*`n_max'),1);


summ vulnmean if id==`n_1l', meanonly;
local vn_1l=r(mean);
summ vulnmean if id==`n_1h', meanonly;
local vn_1h=r(mean);
summ vulnmean if id==`n_5l', meanonly;
local vn_5l=r(mean);
summ vulnmean if id==`n_5h', meanonly;
local vn_5h=r(mean);
summ vulnmean if id==`n_10l', meanonly;
local vn_10l=r(mean);
summ vulnmean if id==`n_10h', meanonly;
local vn_10h=r(mean);


sort povmean;
quietly replace id=_n;
summ povmean if id==`n_1l', meanonly;
local pn_1l=r(mean);
summ povmean if id==`n_1h', meanonly;
local pn_1h=r(mean);
summ povmean if id==`n_5l', meanonly;
local pn_5l=r(mean);
summ povmean if id==`n_5h', meanonly;
local pn_5h=r(mean);
summ povmean if id==`n_10l', meanonly;
local pn_10l=r(mean);
summ povmean if id==`n_10h', meanonly;
local pn_10h=r(mean);


sort riskmean;
quietly replace id=_n;
summ riskmean if id==`n_1l', meanonly;
local rn_1l=r(mean);
summ riskmean if id==`n_1h', meanonly;
local rn_1h=r(mean);
summ riskmean if id==`n_5l', meanonly;
local rn_5l=r(mean);
summ riskmean if id==`n_5h', meanonly;
local rn_5h=r(mean);
summ riskmean if id==`n_10l', meanonly;
local rn_10l=r(mean);
summ riskmean if id==`n_10h', meanonly;
local rn_10h=r(mean);


sort agriskmean;
quietly replace id=_n;
summ agriskmean if id==`n_1l', meanonly;
local an_1l=r(mean)
```

```
summ agriskmean if id==`n_1h', meanonly;
local an_1h=r(mean);
summ agriskmean if id==`n_5l', meanonly;
local an_5l=r(mean);
summ agriskmean if id==`n_5h', meanonly;
local an_5h=r(mean);
summ agriskmean if id==`n_10l', meanonly;
local an_10l=r(mean);
summ agriskmean if id==`n_10h', meanonly;
local an_10h=r(mean);


sort idrisktotmean;
quietly replace id=_n;
summ idrisktotmean if id==`n_1l', meanonly;
local in_1l=r(mean);
summ idrisktotmean if id==`n_1h', meanonly;
local in_1h=r(mean);
summ idrisktotmean if id==`n_5l', meanonly;
local in_5l=r(mean);
summ idrisktotmean if id==`n_5h', meanonly;
local in_5h=r(mean);
summ idrisktotmean if id==`n_10l', meanonly;
local in_10l=r(mean);
summ idrisktotmean if id==`n_10h', meanonly;
local in_10h=r(mean);


forvalues num= 1/`ir_n' {;
  sort idrisk`num'mean;
  quietly replace id=_n;
  summ idrisk`num'mean if id==`n_1l', meanonly;
  local i`num'n_1l=r(mean);
  summ idrisk`num'mean if id==`n_1h', meanonly;
  local i`num'n_1h=r(mean);
  summ idrisk`num'mean if id==`n_5l', meanonly;
  local i`num'n_5l=r(mean);
  summ idrisk`num'mean if id==`n_5h', meanonly;
  local i`num'n_5h=r(mean);
  summ idrisk`num'mean if id==`n_10l', meanonly;
  local i`num'n_10l=r(mean);
  summ idrisk`num'mean if id==`n_10h', meanonly;
  local i`num'n_10h=r(mean);
};


sort unexpriskmean;
quietly replace id=_n;
summ unexpriskmean if id==`n_1l', meanonly;
local un_1l=r(mean);
summ unexpriskmean if id==`n_1h', meanonly;
local un_1h=r(mean);
summ unexpriskmean if id==`n_5l', meanonly;
local un_5l=r(mean);
summ unexpriskmean if id==`n_5h', meanonly;
local un_5h=r(mean);
summ unexpriskmean if id==`n_10l', meanonly;
local un_10l=r(mean);
```

```
summ unexpriskmean if id==`n_10h', meanonly;
local un_10h=r(mean);

display"";
display"";
display as text "Bootstrapped confidence intervals for" _continue;
display " survey means of vulnerability measures.";
display "These take into account sampling weights if specified.";
display"";
display in text "Variable{c |}Pop. Mean [ 90% Conf. Int."_continue;
display "] [ 95% Conf. Int.] [ 99% Conf. Int.]";
display in text "{hline 8}{c +}{hline 63}";
display in text "vulnmean{c |}" as result %8.4g `realvv' "  ["
  %7.3g `vn_10l' ","%7.3g `vn_10h' "] [%7.3g `vn_5l' ","%7.3g `vn_5h'
  "] [%7.3g `vn_1l' "," %7.3g `vn_1h' "]" ;
display in text " povmean{c |}" as result %8.4g `realpp' "  ["
  %7.3g `pn_10l' ","%7.3g `pn_10h' "] [%7.3g `pn_5l' ","%7.3g `pn_5h'
  "] [%7.3g `pn_1l' "," %7.3g `pn_1h' "]" ;
display in text "riskmean{c |}" as result %8.4g `realrr' "  ["
  %7.3g `rn_10l' ","%7.3g `rn_10h' "] [%7.3g `rn_5l' ","%7.3g `rn_5h'
  "] [%7.3g `rn_1l' "," %7.3g `rn_1h' "]" ;
display in text "agrism~n{c |}" as result %8.4g `realaa' "  ["
  %7.3g `an_10l' ","%7.3g `an_10h' "] [%7.3g `an_5l' ","%7.3g `an_5h'
  "] [%7.3g `an_1l' "," %7.3g `an_1h' "]" ;
display in text "idrism~n{c |}" as result %8.4g `realitt' "  ["
  %7.3g `in_10l' ","%7.3g `in_10h' "] [%7.3g `in_5l' ","%7.3g `in_5h'
  "] [%7.3g `in_1l' "," %7.3g `in_1h' "]" ;
forvalues num= 1/`ir_n' {;
  display in text "idri`num'm~n{c |}" as result %8.4g `realii`num''
    "  [%7.3g `i`num'n_10l' ","%7.3g `i`num'n_10h' "] [%7.3g
    `i`num'n_5l' ","%7.3g `i`num'n_5h' "] [%7.3g `i`num'n_1l' ","
    %7.3g `i`num'n_1h' "]" ;
};
display in text "unexri~n{c |}" as result %8.4g `realuu' "  ["
  %7.3g `un_10l' ","%7.3g `un_10h' "] [%7.3g `un_5l' ","%7.3g `un_5h'
  "] [%7.3g `un_1l' "," %7.3g `un_1h' "]" ;

if `runreg'==1 {;
  clear;
  quietly use `regboot1';
  forvalues num2= 1/`ir_n' {;
    merge using `regboot1i`num2'';
    drop _merge;
    merge using `regbootconsti`num2'';
    drop _merge;
  };
  if `rrv_n' >1 {;
    forvalues num=2/`rrv_n' {;
      merge using `regboot`num'';
      drop _merge;
      forvalues num2= 1/`ir_n' {;
        merge using `regboot`num'i`num2'';
        drop _merge;
      };
    };
  };
  merge using `regbootconst';
  drop _merge;
```

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```
gen id=_n;
tempname n_1l n_1h n_5l n_5h n_10l n_10h;
quietly summ id;
local n_max=r(max);
scalar `n_1l'=round((.005*`n_max'),1);
scalar `n_1h'=round((.995*`n_max'),1);
scalar `n_5l'=round((.025*`n_max'),1);
scalar `n_5h'=round((.975*`n_max'),1);
scalar `n_10l'=round((.05*`n_max'),1);
scalar `n_10h'=round((.95*`n_max'),1);


forvalues num= 1/`rrv_n' {;
  sort rrbeta`num'v;
  quietly replace id=_n;
  summ rrbeta`num'v if id==`n_1l', meanonly;
  local r`num'vn_1l=r(mean);
  summ rrbeta`num'v if id==`n_1h', meanonly;
  local r`num'vn_1h=r(mean);
  summ rrbeta`num'v if id==`n_5l', meanonly;
  local r`num'vn_5l=r(mean);
  summ rrbeta`num'v if id==`n_5h', meanonly;
  local r`num'vn_5h=r(mean);
  summ rrbeta`num'v if id==`n_10l', meanonly;
  local r`num'vn_10l=r(mean);
  summ rrbeta`num'v if id==`n_10h', meanonly;
  local r`num'vn_10h=r(mean);
};
sort rrbetaconstv;
quietly replace id=_n;
summ rrbetaconstv if id==`n_1l', meanonly;
local rconstvn_1l=r(mean);
summ rrbetaconstv if id==`n_1h', meanonly;
local rconstvn_1h=r(mean);
summ rrbetaconstv if id==`n_5l', meanonly;
local rconstvn_5l=r(mean);
summ rrbetaconstv if id==`n_5h', meanonly;
local rconstvn_5h=r(mean);
summ rrbetaconstv if id==`n_10l', meanonly;
local rconstvn_10l=r(mean);
summ rrbetaconstv if id==`n_10h', meanonly;
local rconstvn_10h=r(mean);


display"";
display"";
display as text "Bootstrapped vulnerability regression";
display as text "                                                   "
  " No. of obs =" as result %8.0g `Nv';
display as text "                                                   "
  " R-squared  =" as result %8.4g `r2v';
display as text "{hline 6}{c TT}{hline 63}";
display in text "Vuln~y{c |} Coef.  [ 90% "
  "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
display in text "{hline 6}{c +}{hline 63}";
forvalues num= 1/`rrv_n' {;
  display in text %6s abbrev("${namerrv`num'}",6) "{c |}"
    as result %7.3g `realb`num'v'
```

```
          " ["%7.3g `r`num'vn_10l' " ,"%7.3g `r`num'vn_10h' "] ["%7.3g
      `r`num'vn_5l' " ,"%7.3g `r`num'vn_5h' "] ["%7.3g `r`num'vn_1l' " ,"
      %7.3g `r`num'vn_1h' "]" ;
  };
  display as text %6s "_cons""{c |}" as result %7.3g `realbconstv'
    " ["%7.3g `rconstvn_10l' " ,"%7.3g `rconstvn_10h' "] ["%7.3g
    `rconstvn_5l' " ,"%7.3g `rconstvn_5h' "] ["%7.3g `rconstvn_1l' " ,"
    %7.3g `rconstvn_1h' "]" ;
  display as text "{hline 6}{c BT}{hline 63}";


  forvalues num= 1/`rrv_n' {;
    sort rrbeta`num'p;
    quietly replace id=_n;
    summ rrbeta`num'p if id==`n_1l', meanonly;
    local r`num'pn_1l=r(mean);
    summ rrbeta`num'p if id==`n_1h', meanonly;
    local r`num'pn_1h=r(mean);
    summ rrbeta`num'p if id==`n_5l', meanonly;
    local r`num'pn_5l=r(mean);
    summ rrbeta`num'p if id==`n_5h', meanonly;
    local r`num'pn_5h=r(mean);
    summ rrbeta`num'p if id==`n_10l', meanonly;
    local r`num'pn_10l=r(mean);
    summ rrbeta`num'p if id==`n_10h', meanonly;
    local r`num'pn_10h=r(mean);
  };
  sort rrbetaconstp;
  quietly replace id=_n;
  summ rrbetaconstp if id==`n_1l', meanonly;
  local rconstpn_1l=r(mean);
  summ rrbetaconstp if id==`n_1h', meanonly;
  local rconstpn_1h=r(mean);
  summ rrbetaconstp if id==`n_5l', meanonly;
  local rconstpn_5l=r(mean);
  summ rrbetaconstp if id==`n_5h', meanonly;
  local rconstpn_5h=r(mean);
  summ rrbetaconstp if id==`n_10l', meanonly;
  local rconstpn_10l=r(mean);
  summ rrbetaconstp if id==`n_10h', meanonly;
  local rconstpn_10h=r(mean);


  display"";
  display"";
  display as text "Bootstrapped poverty regression";
  display as text "                                                "
    " No. of obs =" as result %8.0g `Nv';
  display as text "                                                "
    " R-squared  =" as result %8.4g `r2p';
  display as text "{hline 6}{c TT}{hline 63}";
  display in text "Pov~ty{c |} Coef.    [ 90% "
    "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
  display in text "{hline 6}{c +}{hline 63}";
  forvalues num= 1/`rrv_n' {;
    display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
      as result %7.3g `realb`num'p'
        " ["%7.3g `r`num'pn_10l' " ,"%7.3g `r`num'pn_10h' "] ["%7.3g
```

```
      `r`num'pn_5l' " ,"%7.3g `r`num'pn_5h' "] [%7.3g `r`num'pn_1l' " ,"
      %7.3g `r`num'pn_1h' "]" ;
   };
   display as text %6s "_cons""{c |}" as result %7.3g `realbconstp'
     " ["%7.3g `rconstpn_10l' " ,"%7.3g `rconstpn_10h' "] ["%7.3g
     `rconstpn_5l' " ,"%7.3g `rconstpn_5h' "] ["%7.3g `rconstpn_1l' " ,"
     %7.3g `rconstpn_1h' "]" ;
   display as text "{hline 6}{c BT}{hline 63}";


   forvalues num= 1/`rrv_n' {;
     sort rrbeta`num'r;
     quietly replace id=_n;
     summ rrbeta`num'r if id==`n_1l', meanonly;
     local r`num'rn_1l=r(mean);
     summ rrbeta`num'r if id==`n_1h', meanonly;
     local r`num'rn_1h=r(mean);
     summ rrbeta`num'r if id==`n_5l', meanonly;
     local r`num'rn_5l=r(mean);
     summ rrbeta`num'r if id==`n_5h', meanonly;
     local r`num'rn_5h=r(mean);
     summ rrbeta`num'r if id==`n_10l', meanonly;
     local r`num'rn_10l=r(mean);
     summ rrbeta`num'r if id==`n_10h', meanonly;
     local r`num'rn_10h=r(mean);
   };
   sort rrbetaconstr;
   quietly replace id=_n;
   summ rrbetaconstr if id==`n_1l', meanonly;
   local rconstrn_1l=r(mean);
   summ rrbetaconstr if id==`n_1h', meanonly;
   local rconstrn_1h=r(mean);
   summ rrbetaconstr if id==`n_5l', meanonly;
   local rconstrn_5l=r(mean);
   summ rrbetaconstr if id==`n_5h', meanonly;
   local rconstrn_5h=r(mean);
   summ rrbetaconstr if id==`n_10l', meanonly;
   local rconstrn_10l=r(mean);
   summ rrbetaconstr if id==`n_10h', meanonly;
   local rconstrn_10h=r(mean);


   display"";
   display"";
   display as text "Bootstrapped risk regression";
   display as text "                                                    "
     " No. of obs =" as result %8.0g `Nv';
   display as text "                                                    "
     " R-squared  =" as result %8.4g `r2r';
   display as text "{hline 6}{c TT}{hline 63}";
   display in text "  Risk{c |} Coef.  [ 90% "
     "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
   display in text "{hline 6}{c +}{hline 63}";
   forvalues num =1/`rrv_n' {;
     display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
       as result %7.3g `realb`num'r'
       " ["%7.3g `r`num'rn_10l' " ,"%7.3g `r`num'rn_10h' "] ["%7.3g
       `r`num'rn_5l' " ,"%7.3g `r`num'rn_5h' "] ["%7.3g `r`num'rn_1l' " ,"
```

```
    %7.3g `r`num'rn_1h' "]" ;
  };
display as text %6s "_cons""{c |}" as result %7.3g `realbconstr'
  " ["%7.3g `rconstrn_10l' " ,"%7.3g `rconstrn_10h' "] ["%7.3g
  `rconstrn_5l' " ,"%7.3g `rconstrn_5h' "] ["%7.3g `rconstrn_1l' " ,"
  %7.3g `rconstrn_1h' "]" ;
display as text "{hline 6}{c BT}{hline 63}";


forvalues num= 1/`rrv_n' {;
  sort rrbeta`num'a;
  quietly replace id=_n;
  summ rrbeta`num'a if id==`n_1l', meanonly;
  local r`num'an_1l=r(mean);
  summ rrbeta`num'a if id==`n_1h', meanonly;
  local r`num'an_1h=r(mean);
  summ rrbeta`num'a if id==`n_5l', meanonly;
  local r`num'an_5l=r(mean);
  summ rrbeta`num'a if id==`n_5h', meanonly;
  local r`num'an_5h=r(mean);
  summ rrbeta`num'a if id==`n_10l', meanonly;
  local r`num'an_10l=r(mean);
  summ rrbeta`num'a if id==`n_10h', meanonly;
  local r`num'an_10h=r(mean);
};
sort rrbetaconsta;
quietly replace id=_n;
summ rrbetaconsta if id==`n_1l', meanonly;
local rconstan_1l=r(mean);
summ rrbetaconsta if id==`n_1h', meanonly;
local rconstan_1h=r(mean);
summ rrbetaconsta if id==`n_5l', meanonly;
local rconstan_5l=r(mean);
summ rrbetaconsta if id==`n_5h', meanonly;
local rconstan_5h=r(mean);
summ rrbetaconsta if id==`n_10l', meanonly;
local rconstan_10l=r(mean);
summ rrbetaconsta if id==`n_10h', meanonly;
local rconstan_10h=r(mean);


display"";
display"";
display as text "Bootstrapped aggregate risk regression";
display as text "                                                 "
  " No. of obs =" as result %8.0g `Nv';
display as text "                                                 "
  " R-squared  =" as result %8.4g `r2a';
display as text "{hline 6}{c TT}{hline 63}";
display in text "AggRis{c |} Coef.   [ 90% "
  "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
display in text "{hline 6}{c +}{hline 63}";
forvalues num= 1/`rrv_n' {;
  display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
    as result %7.3g `realb`num'a'
    " ["%7.3g `r`num'an_10l' " ,"%7.3g `r`num'an_10h' "] ["%7.3g
    `r`num'an_5l' " ,"%7.3g `r`num'an_5h' "] ["%7.3g `r`num'an_1l' " ,"
    %7.3g `r`num'an_1h' "]" ;
```

```
};
display as text %6s "_cons""{c |}" as result %7.3g `realbconsta'
  " ["%7.3g `rconstan_10l' " ,"%7.3g `rconstan_10h' "] ["%7.3g
  `rconstan_5l' " ,"%7.3g `rconstan_5h' "] ["%7.3g `rconstan_1l' " ,"
  %7.3g `rconstan_1h' "]" ;
display as text "{hline 6}{c BT}{hline 63}";


forvalues num =1/`rrv_n' {;
  sort rrbeta`num'it;
  quietly replace id=_n;
  summ rrbeta`num'it if id==`n_1l', meanonly;
  local r`num'itn_1l=r(mean);
  summ rrbeta`num'it if id==`n_1h', meanonly;
  local r`num'itn_1h=r(mean);
  summ rrbeta`num'it if id==`n_5l', meanonly;
  local r`num'itn_5l=r(mean);
  summ rrbeta`num'it if id==`n_5h', meanonly;
  local r`num'itn_5h=r(mean);
  summ rrbeta`num'it if id==`n_10l', meanonly;
  local r`num'itn_10l=r(mean);
  summ rrbeta`num'it if id==`n_10h', meanonly;
  local r`num'itn_10h=r(mean);
};
sort rrbetaconstit;
quietly replace id=_n;
summ rrbetaconstit if id==`n_1l', meanonly;
local rconstitn_1l=r(mean);
summ rrbetaconstit if id==`n_1h', meanonly;
local rconstitn_1h=r(mean);
summ rrbetaconstit if id==`n_5l', meanonly;
local rconstitn_5l=r(mean);
summ rrbetaconstit if id==`n_5h', meanonly;
local rconstitn_5h=r(mean);
summ rrbetaconstit if id==`n_10l', meanonly;
local rconstitn_10l=r(mean);
summ rrbetaconstit if id==`n_10h', meanonly;
local rconstitn_10h=r(mean);

display"";
display"";
display as text "Bootstrapped total idiosyncratic risk regression";
display as text "                                                 "
  " No. of obs =" as result %8.0g `Ni';
display as text "                                                 "
  " R-squared  =" as result %8.4g `r2it';
display as text "{hline 6}{c TT}{hline 63}";
display in text "IdRisk{c |} Coef.  [ 90% "
  "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
display in text "{hline 6}{c +}{hline 63}";
forvalues num= 1/`rrv_n' {;
  display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
    as result %7.3g `realb`num'it'
    " ["%7.3g `r`num'itn_10l' " ,"%7.3g `r`num'itn_10h' "] ["%7.3g
    `r`num'itn_5l' " ,"%7.3g `r`num'itn_5h' "] ["%7.3g `r`num'itn_1l'
    " ," %7.3g `r`num'itn_1h' "]" ;
};
display as text %6s "_cons""{c |}" as result %7.3g `realbconstit'
```

```
            " [%7.3g `rconstitn_10l' " ,"%7.3g `rconstitn_10h' "] ["%7.3g
            `rconstitn_5l' " ,"%7.3g `rconstitn_5h' "] ["%7.3g `rconstitn_1l' " ,"
            %7.3g `rconstitn_1h' "]" ;
        display as text "{hline 6}{c BT}{hline 63}";


    forvalues num2= 1/`ir_n' {;
        forvalues num= 1/`rrv_n' {;
            sort rrbeta`num'i`num2';
            quietly replace id=_n;
            summ rrbeta`num'i`num2' if id==`n_1l', meanonly;
            local r`num'i`num2'n_1l=r(mean);
            summ rrbeta`num'i`num2' if id==`n_1h', meanonly;
            local r`num'i`num2'n_1h=r(mean);
            summ rrbeta`num'i`num2' if id==`n_5l', meanonly;
            local r`num'i`num2'n_5l=r(mean);
            summ rrbeta`num'i`num2' if id==`n_5h', meanonly;
            local r`num'i`num2'n_5h=r(mean);
            summ rrbeta`num'i`num2' if id==`n_10l', meanonly;
            local r`num'i`num2'n_10l=r(mean);
            summ rrbeta`num'i`num2' if id==`n_10h', meanonly;
            local r`num'i`num2'n_10h=r(mean);
        };
        sort rrbetaconsti`num2';
        quietly replace id=_n;
        summ rrbetaconsti`num2' if id==`n_1l', meanonly;
        local rconsti`num2'n_1l=r(mean);
        summ rrbetaconsti`num2' if id==`n_1h', meanonly;
        local rconsti`num2'n_1h=r(mean);
        summ rrbetaconsti`num2' if id==`n_5l', meanonly;
        local rconsti`num2'n_5l=r(mean);
        summ rrbetaconsti`num2' if id==`n_5h', meanonly;
        local rconsti`num2'n_5h=r(mean);
        summ rrbetaconsti`num2' if id==`n_10l', meanonly;
        local rconsti`num2'n_10l=r(mean);
        summ rrbetaconsti`num2' if id==`n_10h', meanonly;
        local rconsti`num2'n_10h=r(mean);

        display"";
        display"";
        display as text "Bootstrapped idiosyncratic risk #" `num2' "regression";
        display as text "                                                      "
            " No. of obs =" as result %8.0g `Ni';
        display as text "                                                      "
            " R-squared  =" as result %8.4g `r2i`num2'';
        display as text "{hline 6}{c TT}{hline 63}";
        display in text "IdRis" `num2' "{c |} Coef. [ 90% "
            "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
        display in text "{hline 6}{c +}{hline 63}";
        forvalues num= 1/`rrv_n' {;
            display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
                as result %7.3g `realb`num'i`num2''
                " ["%7.3g `r`num'i`num2'n_10l' " ,"%7.3g `r`num'i`num2'n_10h'
                "] ["%7.3g `r`num'i`num2'n_5l' " ,"%7.3g `r`num'i`num2'n_5h'
                "] ["%7.3g `r`num'i`num2'n_1l' " ," %7.3g `r`num'i`num2'n_1h' "]" ;
        };
        display as text %6s "_cons""{c |}" as result %7.3g
            `realbconsti`num2''
```

```
      " ["%7.3g `rconsti`num2'n_10l' " ,"%7.3g `rconsti`num2'n_10h'
      "] ["%7.3g `rconsti`num2'n_5l' " ,"%7.3g `rconsti`num2'n_5h'
      "] ["%7.3g `rconsti`num2'n_1l' " ," %7.3g `rconsti`num2'n_1h' "]" ;
  display as text "{hline 6}{c BT}{hline 63}";
};


forvalues num= 1/`rrv_n' {;
  sort rrbeta`num'u;
  quietly replace id=_n;
  summ rrbeta`num'u if id==`n_1l', meanonly;
  local r`num'un_1l=r(mean);
  summ rrbeta`num'u if id==`n_1h', meanonly;
  local r`num'un_1h=r(mean);
  summ rrbeta`num'u if id==`n_5l', meanonly;
  local r`num'un_5l=r(mean);
  summ rrbeta`num'u if id==`n_5h', meanonly;
  local r`num'un_5h=r(mean);
  summ rrbeta`num'u if id==`n_10l', meanonly;
  local r`num'un_10l=r(mean);
  summ rrbeta`num'u if id==`n_10h', meanonly;
  local r`num'un_10h=r(mean);
};


sort rrbetaconstu;
quietly replace id=_n;
summ rrbetaconstu if id==`n_1l', meanonly;
local rconstun_1l=r(mean);
summ rrbetaconstu if id==`n_1h', meanonly;
local rconstun_1h=r(mean);
summ rrbetaconstu if id==`n_5l', meanonly;
local rconstun_5l=r(mean);
summ rrbetaconstu if id==`n_5h', meanonly;
local rconstun_5h=r(mean);
summ rrbetaconstu if id==`n_10l', meanonly;
local rconstun_10l=r(mean);
summ rrbetaconstu if id==`n_10h', meanonly;
local rconstun_10h=r(mean);


display"";
display"";
display as text "Bootstrapped unexplained risk regression";
display as text "                                                     "
  " No. of obs =" as result %8.0g `Ni';
display as text "                                                     "
  " R-squared  =" as result %8.4g `r2u';
display as text "{hline 6}{c TT}{hline 63}";
display in text "UnxRis{c |} Coef.  [ 90% "
  "Conf. Int. ] [ 95% Conf. Int. ] [ 99% Conf. Int. ]";
display in text "{hline 6}{c +}{hline 63}";
forvalues num= 1/`rrv_n' {;
  display as text %6s abbrev("${namerrv`num'}",6) "{c |}"
    as result %7.3g `realb`num'u'
    " ["%7.3g `r`num'un_10l' " ,"%7.3g `r`num'un_10h' "] ["%7.3g
    `r`num'un_5l' " ,"%7.3g `r`num'un_5h' "] ["%7.3g `r`num'un_1l' " ,"
    %7.3g `r`num'un_1h' "]" ;
};
```

```
      display as text %6s "_cons""{c |}" as result %7.3g `realbconstu'
        " ["%7.3g `rconstun_10l' " ,"%7.3g `rconstun_10h' "] ["%7.3g
        `rconstun_5l' " ,"%7.3g `rconstun_5h' "] ["%7.3g `rconstun_1l' " ,"
        %7.3g `rconstun_1h' "]" ;
      display as text "{hline 6}{c BT}{hline 63}";
      restore;
    };
  };


  if `boot'==0 & `runreg'==1 {;
    display"";
    display"";
    display as text "Non-bootstrapped vulnerability regression";
    display"";
    display as text "                                                    "
      " No. of obs =" as result %8.0g $Nv;
    display as text "                                                    "
      " R-squared  =" as result %8.4g $r2v;
    display as text "{hline 16}{c TT}{hline 53}";
    display in text "    Vulnerability{c |} Coefficient";
    display in text "{hline 16}{c +}{hline 53}";
    forvalues num= 1/`rrv_n' {;
      display in text %16s abbrev("${namerrv`num'}",16) "{c |}"
        as result %8.4g `realb`num'v';
    };
    display as text %16s "_cons""{c |}" as result %7.3g `realbconstv';
    display as text "{hline 16}{c BT}{hline 53}";

    display"";
    display"";
    display as text "Non-bootstrapped poverty regression";
    display"";
    display as text "                                                    "
      " No. of obs =" as result %8.0g $Nv;
    display as text "                                                    "
      " R-squared  =" as result %8.4g $r2p;
    display as text "{hline 16}{c TT}{hline 53}";
    display in text "         Poverty{c |} Coefficient";
    display in text "{hline 16}{c +}{hline 53}";
    forvalues num= 1/`rrv_n' {;
      display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
        as result %8.4g `realb`num'p';
    };
    display as text %16s "_cons""{c |}" as result %8.4g `realbconstp';
    display as text "{hline 16}{c BT}{hline 53}";

    display"";
    display"";
    display as text "Non-bootstrapped risk regression";
    display"";
    display as text "                                                    "
      " No. of obs =" as result %8.0g $Nv;
    display as text "                                                    "
      " R-squared  =" as result %8.4g $r2r;
    display as text "{hline 16}{c TT}{hline 53}";
    display in text "            Risk{c |} Coefficient";
    display in text "{hline 16}{c +}{hline 53}";
```

```
forvalues num =1/`rrv_n' {;
  display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
    as result %8.4g `realb`num'r';
};
display as text %16s "_cons""{c |}" as result %8.4g `realbconstr';
display as text "{hline 16}{c BT}{hline 53}";

display"";
display"";
display as text "Non-bootstrapped aggregate risk regression";
display"";
display as text "                                             "
  " No. of obs =" as result %8.0g $Nv;
display as text "                                             "
  " R-squared  =" as result %8.4g $r2a;
display as text "{hline 16}{c TT}{hline 53}";
display in text "  Aggregate Risk{c |} Coefficient";
display in text "{hline 16}{c +}{hline 53}";
forvalues num= 1/`rrv_n' {;
  display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
    as result %8.4g `realb`num'a';
};
display as text %16s "_cons""{c |}" as result %8.4g `realbconsta';
display as text "{hline 16}{c BT}{hline 53}";

display"";
display"";
display as text "Non-bootstrapped total idiosyncratic risk regression";
display"";
display as text "                                             "
  " No. of obs =" as result %8.0g $Ni;
display as text "                                             "
  " R-squared  =" as result %8.4g $r2it;
display as text "{hline 16}{c TT}{hline 53}";
display in text "  Idiosync. Risk{c |} Coefficient";
display in text "{hline 16}{c +}{hline 53}";
forvalues num= 1/`rrv_n' {;
  display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
    as result %8.4g `realb`num'it';
};
display as text %16s "_cons""{c |}" as result %8.4g `realbconstit';
display as text "{hline 16}{c BT}{hline 53}";

forvalues num2=1/`ir_n' {;
  display"";
  display"";
  display as text "Non-bootstrapped idiosyncratic risk #" `num2' "
regression";
  display"";
  display as text "                                             "
    " No. of obs =" as result %8.0g $Ni;
  display as text "                                             "
    " R-squared  =" as result %8.4g ${r2i`num2'};
  display as text "{hline 16}{c TT}{hline 53}";
  display in text "Idiosyn. Risk #" `num2' "{c |} Coefficient";
  display in text "{hline 16}{c +}{hline 53}";
  forvalues num= 1/`rrv_n' {;
    display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
```

```
        as result %8.4g `realb`num'i`num2'';
    };
    display as text %16s "_cons""{c |}" as result %8.4g
      `realbconsti`num2'';
    display as text "{hline 16}{c BT}{hline 53}";
};

display"";
display"";
display as text "Non-bootstrapped unexplained risk regression";
display"";
display as text "                                              "
   " No. of obs =" as result %8.0g $Ni;
display as text "                                              "
   " R-squared  =" as result %8.4g $r2u;
display as text "{hline 16}{c TT}{hline 53}";
display in text "Unexplained Risk{c |} Coefficient";
display in text "{hline 16}{c +}{hline 53}";
forvalues num= 1/`rrv_n' {;
  display as text %16s abbrev("${namerrv`num'}",16) "{c |}"
     as result %8.4g `realb`num'u';
};
display as text %16s "_cons""{c |}" as result %8.4g `realbconstu';
display as text "{hline 16}{c BT}{hline 53}";end;
```

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vulnerability.hlp

```
help for ^vulnerability^
```

Calculating vulnerability in a population
```
    ^vulnerability^ i t c [varlist] [^if^ exp] ^[pweight=^varname^]^
        [^,gamma(^#^) z(^#^) boot(^#^) nreps(^#^) runregvar(^varlist^)^]
```

The variables required by ^vulnerability^ are i (household identification
   variable name) t (time period variable name) c (consumption variable
   name). Idioysncratic risk variables are optional and should be
   included in varlist.

Description
^vulnerability^ calculates vulnerability, risk, aggregate risk,
    idiosyncratic risk, (and its components), and unexplained risk
    variables (as described in Ligon-Schechter '03). It also gives
    the user the option to bootstrap confidence intervals for average
    vulnerability measures in the population and to run bootstrapped
    regressions to find the correlates of these vulnerability measures.
Consumption and income variables must be in real per-capita terms.
The panel data should be in `long' form; see help @reshape@. This code will
    work with an unbalanced panel, but will ignore those households with
    missing observations on consumption. It will also ignore households
    with negative or zero consumption in any period. This code will
    calculate vulnerability, poverty, risk, and aggregate risk, but not
    idiosyncratic risk or unexplained risk, for those households which
    have missing data for one of the idiosyncratic risk variables.
You are allowed to enter any number of variables which represent
    idiosyncratic risk. These variables must vary over time, and if
    you are including a variable such as income it should be in real
    per capita terms.
Note that this code creates variables called vulnerability, poverty,
    risk, agrisk, idrisktot, unexprisk and idrisk1-N. If you already
    have a variable with one of those names the program will say,
    e.g. "vulnerability already defined". If you would like to calculate
    vulnerability twice, for example once using total consumption and
    then again using food consumption, you should run the code once and
    then rename the output variables before running it the second time.

Options
^gamma(^#^)^ specifies the constant of relative risk aversion. The default
    for gamma is 2, though any real number greater than or equal to 1
    is permitted. For gamma=1 the utility function is log utility. For
    gamma>1 the utility function is CRS with CRRA of gamma.
^z(^#^)^ specifies whether vulnerability will be calculated with respect
    to a poverty line, or with respect to average consumption. For z=0
    average consumption is used as the reference point. Thus relative
    vulnerability is calculated. For z~=0, z should be the poverty line.
    The default is z=0.
^boot(^#^)^ specifies whether or not to run a bootstrap. boot(0) does
    not run the bootstrap and boot(1) does run the bootstrap. The default
    is boot(0).
^nreps(^#^)^ specifies the nuber of repetitions to be used in the bootstrap.
    The default is 1000 repetitions.
^runregvar(^varlist^)^ specifies that you would like to run a regression
    of the vulnerability measures on the household averages of the variables
    in varlist. Because each household's vulnerability is constant over time,

the mean of the LHS variables will be used. The number of observarions
will thus be the number of households. Also, because the vulnerability
measures are themselves estimates, standard errors and confidence
intervals will not be shown if boot(1) was not specified.
^if^ exp is allowed as with other Stata commands.
^[pweight=^varname^]^ specifies that sampling weights should be used.
This option does tend to make the bootstrap slower.

Examples
    ^. vulnerability hhid month cons^
    ^. vulnerability hhid month cons [pweight=w]^
    ^. vulnerability hhid month cons inc unemploy pension^
    ^. vulnerability hhid month cons inc unemp pens, gamma(2) z(0)^
    ^. vulnerability hhid month cons inc unemp pens, gamma(1) z(1525)^
    ^. vulnerability hhid month cons inc unemp pens, boot(1) nreps(10000)^
          ^runregvar(region male educ age rural)^

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bangla_risk.do

```
/*hhshock.do*/
/*this file estimates basic consumption smoothing model with expenditures as a
function of shocks
site and round dummies*/
capture log close
#delimit;
log using d:\vulnerability\toolkit\bangla, replace text;
set mem 40m;
use d:\vulnerability\toolkit\bangla;

***************************************************
*variable definitions                            *
*newunion  = union (or village);
*rnd= round;
*sl = household number;
*lincome= log monthly income;
*lmcons=log monthly consumption;
*lmfood=log monthly food consumption;
*lmnfood=log monthly nonfood consumption;
*tmem=total household members;
*femhead=dummy for female headed household;
*headage=age of household head;
*headage2=age of hh head squared;
*lrent=land rental income;
*rental=other rental income;
*dowry=dowry receipts;
*************defining shocks vectors***************
*llivedead=log of value of livestock deaths;
*illf2wk=illness days of adult females in last two weeks;
*illm2wk=illness days of adult males in last two weeks;
***********income components for instruments***************
*lrent=land rental income;
*rental=other rental income;
*dowry=dowry receipts;
* nonfoody=(lrent+rental+dowry)/tmem;
* lnonfoody=ln(nonfoody+1);

by newunion rnd, sort: egen meanlinc=mean(lincome);

/*first take first differences*/
sort sl rnd;
quietly by sl: gen dlmcons=lmcons[_n]-lmcons[_n-1];
quietly by sl: gen dlmfood=lmfood[_n]-lmfood[_n-1];
quietly by sl: gen dlmnfood=lmnfood[_n]-lmnfood[_n-1];
quietly by sl: gen dlincome=lincome[_n]-lincome[_n-1];
quietly by sl: gen dtmem=tmem[_n]-tmem[_n-1];
quietly by sl: gen dmeanlinc=meanlinc[_n]-meanlinc[_n-1];
quietly by sl: gen dlnonfoody=lnonfoody[_n]-lnonfoody[_n-1];

**************define right hand side variables********************

global xvec1="femhead headage headage2 dtmem";
global shocks="llivedead illf2wk illm2wk";

****1. first estimate change in consumption as a function of specific shocks;
```

```
/******generate roundx union dummies*******/
egen unirnd=group(newunion rnd);

areg dlmcons $xvec1 $shocks, absorb(unirnd) robust;
areg dlmcons $xvec1 $shocks, absorb(unirnd);


/*disaggregate into food and nonfood*/
/*food expenditures*/
areg dlmfood $xvec1 $shocks, absorb(unirnd) robust;
areg dlmfood $xvec1 $shocks, absorb(unirnd);

/*nonfood*/

areg dlmnfood $xvec1 $shocks, absorb(unirnd) robust;
areg dlmnfood $xvec1 $shocks, absorb(unirnd);


*****2. estimate change in consumption as a function of idiosyncratic income
changes;
/*initial runs--change in consumption and change in income*/
areg dlmcons dlincome $xvec1 , absorb(unirnd) robust;
areg dlmcons dlincome $xvec1 , absorb(unirnd);



/*disaggregate into food and nonfood*/
/*food expenditures*/
areg dlmfood dlincome $xvec1 , absorb(unirnd) robust;
areg dlmfood dlincome $xvec1 , absorb(unirnd);

/*nonfood*/
areg dlmnfood dlincome $xvec1 , absorb(unirnd) robust;
areg dlmnfood dlincome $xvec1 , absorb(unirnd);

******3.  test whether consumption varies with community income;

/*add change in community income*/

regress dlmcons dlincome dmeanlinc $xvec1 , robust;


/*disaggregate into food and nonfood*/
/*food expenditures*/
regress dlmfood dlincome dmeanlinc $xvec1 , robust;

/*nonfood*/
regress dlmnfood dlincome dmeanlinc $xvec1 , robust;

*******4.  do instrumental variables estimates, with idiosyncratic shocks and
nonfood income
components as as instruments for income;

global xvec1="femhead headage headage2 dtmem";
global shocks="llivedead illf2wk illm2wk";
global ivar1="femhead headage headage2 dlnonfoody dtmem ";
```

```
/*instrumental variables estimates*/
areg dlincome $ivar1 $shocks, absorb(unirnd);
test dlnonfoody llivedead illf2wk illm2wk;
predict ehat, resid;



/*initial runs--change in consumption and change in income*/
areg dlmcons dlincome $xvec1 $shocks ehat, absorb(unirnd) robust;

/*disaggregate into food and nonfood; stick with 14 days illness?*/
/*food expenditures*/
areg dlmfood dlincome $xvec1 $shocks ehat , absorb(unirnd) robust;

/*nonfood*/
areg dlmnfood dlincome $xvec1 $shocks ehat , absorb(unirnd) robust;
log close;
```

bangla.log
----
log: d:\vulnerability\toolkit\bangla.log
  log type: text
 opened on: 21 May 2003, 14:53:46

. use d:\vulnerability\toolkit\bangla;

. **
> *variable definitions   *
> *newunion = union (or village);
. *rnd= round;
. *sl = household number;
. *lincome= log monthly income;
. *lmcons=log monthly consumption;
. *lmfood=log monthly food consumption;
. *lmnfood=log monthly nonfood consumption;
. *tmem=total household members;
. *femhead=dummy for female headed household;
. *headage=age of household head;
. *headage2=age of hh head squared;
. *lrent=land rental income;
. *rental=other rental income;
. *dowry=dowry receipts;
. *************defining shocks vectors**************
> *llivedead=log of value of livestock deaths;
. *illf2wk=illness days of adult females in last two weeks;
. *illm2wk=illness days of adult males in last two weeks;
. ***********income components for instruments****************
> *lrent=land rental income;
. *rental=other rental income;
. *dowry=dowry receipts;
. * nonfoody=(lrent+rental+dowry)/tmem;
. * lnonfoody=ln(nonfoody+1);
. by newunion rnd, sort: egen meanlinc=mean(lincome);

. /*first take first differences*/
> sort sl rnd;
. quietly by sl: gen dlmcons=lmcons[_n]-lmcons[_n-1];
. quietly by sl: gen dlmfood=lmfood[_n]-lmfood[_n-1];
. quietly by sl: gen dlmnfood=lmnfood[_n]-lmnfood[_n-1];
. quietly by sl: gen dlincome=lincome[_n]-lincome[_n-1];
. quietly by sl: gen dtmem=tmem[_n]-tmem[_n-1];
. quietly by sl: gen dmeanlinc=meanlinc[_n]-meanlinc[_n-1];
. quietly by sl: gen dlnonfoody=lnonfoody[_n]-lnonfoody[_n-1];

. **************define right hand side variables*******************
> global xvec1="femhead headage headage2 dtmem";
. global shocks="llivedead illf2wk illm2wk";

. ****1. first estimate change in consumption as a function of specific shocks;
. /******generate roundx union dummies*******/
> egen unirnd=group(newunion rnd);

```
. areg dlmcons $xvec1 $shocks, absorb(unirnd) robust;
Regression with robust standard errors                    Number of obs =     2662
                                                          F(  3,  2608) =     1.07
                                                          Prob > F      =   0.3609
                                                          R-squared     =   0.0451
                                                          Adj R-squared =   0.0257
                                                          Root MSE      =  .50669
------------------------------------------------------------------------------
             |               Robust
     dlmcons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    llivedead |     .002711   .0069357     0.39   0.696    -.0108892    .0163111
      illf2wk |   -.0004784   .0058114    -0.08   0.934    -.0118739     .010917
      illm2wk |    .0120277   .0069164     1.74   0.082    -.0015346     .02559
        _cons |   -.0428481   .0125244    -3.42   0.001    -.0674069   -.0182892
-------------+----------------------------------------------------------------
       unirnd |   absorbed                                       (51 categories)

. areg dlmcons $xvec1 $shocks, absorb(unirnd);
                                                          Number of obs =     2662
                                                          F(  3,  2608) =     1.22
                                                          Prob > F      =   0.3012
                                                          R-squared     =   0.0451
                                                          Adj R-squared =   0.0257
                                                          Root MSE      =  .50669
------------------------------------------------------------------------------
     dlmcons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    llivedead |     .002711     .00703     0.39   0.700     -.011074    .0164959
      illf2wk |   -.0004784   .0056242    -0.09   0.932    -.0115069     .01055
      illm2wk |    .0120277   .0064439     1.87   0.062     -.000608    .0246634
        _cons |   -.0428481    .012426    -3.45   0.001    -.0672138   -.0184823
-------------+----------------------------------------------------------------
       unirnd |    F(50, 2608) =     2.410   0.000             (51 categories)

. /*disaggregate into food and nonfood*/
> /*food expenditures*/
> areg dlmfood $xvec1 $shocks, absorb(unirnd) robust;

Regression with robust standard errors                    Number of obs =     2661
                                                          F(  3,  2607) =     1.51
                                                          Prob > F      =   0.2110
                                                          R-squared     =   0.0899
                                                          Adj R-squared =   0.0714
                                                          Root MSE      =  .48157
------------------------------------------------------------------------------
             |               Robust
     dlmfood |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    llivedead |     .007019   .0066685     1.05   0.293    -.0060571    .0200951
      illf2wk |   -.0015613   .0061823    -0.25   0.801     -.013684    .0105613
      illm2wk |    .0120009   .0065825     1.82   0.068    -.0009066    .0249084
        _cons |   -.0622955   .0119814    -5.20   0.000    -.0857894   -.0388015
-------------+----------------------------------------------------------------
       unirnd |   absorbed                                       (51 categories)
```

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```
. areg dlmfood $xvec1 $shocks, absorb(unirnd);
                                                    Number of obs =     2661
                                                    F(  3,  2607) =     1.67
                                                    Prob > F      =   0.1709
                                                    R-squared     =   0.0899
                                                    Adj R-squared =   0.0714
                                                    Root MSE      =   .48157
------------+----------------------------------------------------------------
    dlmfood |      Coef.   Std. Err.       t    P>|t|    [95% Conf. Interval]
------------+----------------------------------------------------------------
   llivedead |    .007019   .0066816     1.05   0.294    -.0060828    .0201207
     illf2wk |  -.0015613   .0053459    -0.29   0.770    -.0120439    .0089212
     illm2wk |   .0120009   .0061248     1.96   0.050    -9.15e-06     .024011
       _cons |  -.0622955   .0118137    -5.27   0.000    -.0854606   -.0391303
------------+----------------------------------------------------------------
      unirnd |     F(50, 2607) =       5.075   0.000           (51 categories)

. /*nonfood*/
> areg dlmnfood $xvec1 $shocks, absorb(unirnd) robust;

Regression with robust standard errors            Number of obs =     2664
                                                  F(  3,  2610) =     0.05
                                                  Prob > F      =   0.9843
                                                  R-squared     =   0.0506
                                                  Adj R-squared =   0.0313
                                                  Root MSE      =   .84073
------------+----------------------------------------------------------------
            |               Robust
    dlmnfood |      Coef.   Std. Err.       t    P>|t|    [95% Conf. Interval]
------------+----------------------------------------------------------------
   llivedead |   .0003428   .0134249     0.03   0.980    -.0259818    .0266673
     illf2wk |   .0001023   .0093174     0.01   0.991    -.0181679    .0183726
     illm2wk |   .0044377   .0114045     0.39   0.697    -.0179251    .0268004
       _cons |   .0094529   .0205006     0.46   0.645    -.0307462    .0496519
------------+----------------------------------------------------------------
      unirnd |  absorbed                                        (51 categories)

. areg dlmnfood $xvec1 $shocks, absorb(unirnd);
                                                    Number of obs =     2664
                                                    F(  3,  2610) =     0.06
                                                    Prob > F      =   0.9814
                                                    R-squared     =   0.0506
                                                    Adj R-squared =   0.0313
                                                    Root MSE      =   .84073
------------+----------------------------------------------------------------
    dlmnfood |      Coef.   Std. Err.       t    P>|t|    [95% Conf. Interval]
------------+----------------------------------------------------------------
   llivedead |   .0003428   .0116647     0.03   0.977    -.0225302    .0232157
     illf2wk |   .0001023   .0093317     0.01   0.991    -.0181959    .0184006
     illm2wk |   .0044377   .0106916     0.42   0.678    -.0165272    .0254026
       _cons |   .0094529   .0206093     0.46   0.647    -.0309594    .0498651
------------+----------------------------------------------------------------
      unirnd |     F(50, 2610) =       2.746   0.000           (51 categories)

. *****2. estimate change in consumption as a function of idiosyncratic income
changes;
. /*initial runs--change in consumption and change in income*/
> areg dlmcons dlincome $xvec1 , absorb(unirnd) robust;
```

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```
Regression with robust standard errors                Number of obs =    2765
                                                      F(  1,  2713) =   12.01
                                                      Prob > F      =  0.0005
                                                      R-squared     =  0.0494
                                                      Adj R-squared =  0.0315
                                                      Root MSE      =  .51153
------------------------------------------------------------------------------
             |               Robust
     dlmcons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dlincome |   .0463175   .0133667     3.47   0.001     .0201075    .0725275
       _cons |  -.0249576   .0099164    -2.52   0.012    -.0444021    -.005513
-------------+----------------------------------------------------------------
      unirnd |   absorbed                                      (51 categories)

. areg dlmcons dlincome $xvec1 , absorb(unirnd);
                                                      Number of obs =    2765
                                                      F(  1,  2713) =   15.82
                                                      Prob > F      =  0.0001
                                                      R-squared     =  0.0494
                                                      Adj R-squared =  0.0315
                                                      Root MSE      =  .51153
------------------------------------------------------------------------------
     dlmcons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dlincome |   .0463175    .011644     3.98   0.000     .0234856    .0691494
       _cons |  -.0249576   .0099842    -2.50   0.012    -.0445349   -.0053802
-------------+----------------------------------------------------------------
      unirnd |    F(50, 2713) =      2.333   0.000           (51 categories)

. /*disaggregate into food and nonfood*/
> /*food expenditures*/
> areg dlmfood dlincome $xvec1 , absorb(unirnd) robust;

Regression with robust standard errors                Number of obs =    2758
                                                      F(  1,  2706) =    8.55
                                                      Prob > F      =  0.0035
                                                      R-squared     =  0.0885
                                                      Adj R-squared =  0.0713
                                                      Root MSE      =   .4978
------------------------------------------------------------------------------
             |               Robust
     dlmfood |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dlincome |   .0375731   .0128506     2.92   0.003      .012375    .0627711
       _cons |  -.0475141   .0096523    -4.92   0.000    -.0664407   -.0285876
-------------+----------------------------------------------------------------
      unirnd |   absorbed                                      (51 categories)

. areg dlmfood dlincome $xvec1 , absorb(unirnd);
                                                      Number of obs =    2758
                                                      F(  1,  2706) =   10.98
                                                      Prob > F      =  0.0009
                                                      R-squared     =  0.0885
                                                      Adj R-squared =  0.0713
                                                      Root MSE      =   .4978
```

```
------------------------------------------------------------------------
     dlmfood |     Coef.   Std. Err.      t     P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------
    dlincome |   .0375731    .011337     3.31   0.001     .015343    .0598032
       _cons |  -.0475141   .0097291    -4.88   0.000    -.0665914   -.0284369
-------------+----------------------------------------------------------
      unirnd |     F(50, 2706) =      4.675   0.000        (51 categories)

.                       /*nonfood*/
> areg dlmnfood dlincome $xvec1 , absorb(unirnd) robust;
Regression with robust standard errors              Number of obs =     2762
                                                    F(  1,  2710) =    12.75
                                                    Prob > F      =   0.0004
                                                    R-squared     =   0.0569
                                                    Adj R-squared =   0.0391
                                                    Root MSE      =   .83385


------------------------------------------------------------------------
             |              Robust
    dlmnfood |     Coef.   Std. Err.      t     P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------
    dlincome |   .0765759   .0214484     3.57   0.000     .0345191    .1186327
       _cons |   .0305567   .0161261     1.89   0.058    -.001064    .0621774
-------------+----------------------------------------------------------
      unirnd |  absorbed                                  (51 categories)

. areg dlmnfood dlincome $xvec1 , absorb(unirnd);

                                                    Number of obs =     2762
                                                    F(  1,  2710) =    16.28
                                                    Prob > F      =   0.0001
                                                    R-squared     =   0.0569
                                                    Adj R-squared =   0.0391
                                                    Root MSE      =   .83385
------------------------------------------------------------------------
    dlmnfood |     Coef.   Std. Err.      t     P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------
    dlincome |   .0765759   .0189814     4.03   0.000     .0393565    .1137953
       _cons |   .0305567   .0162875     1.88   0.061    -.0013805    .0624939
-------------+----------------------------------------------------------
      unirnd |     F(50, 2710) =      2.772   0.000        (51 categories)

.    ******3.  test whether consumption varies with community income;
.                /*add change in community income*/
> regress dlmcons dlincome dmeanlinc $xvec1 , robust;
Regression with robust standard errors              Number of obs =     2765
                                                    F(  2,  2762) =    13.51
                                                    Prob > F      =   0.0000
                                                    R-squared     =   0.0109
                                                    Root MSE      =   .51712

------------------------------------------------------------------------
             |              Robust
     dlmcons |     Coef.   Std. Err.      t     P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------
    dlincome |   .0457206   .0133366     3.43   0.001     .0195699    .0718713
   dmeanlinc |   .1038061   .0387863     2.68   0.007     .027753    .1798592
       _cons |  -.0053496   .0120821    -0.44   0.658    -.0290405    .0183413
------------------------------------------------------------------------
```

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```
.  /*disaggregate into food and nonfood*/
> /*food expenditures*/
> regress dlmfood dlincome dmeanlinc $xvec1 , robust;

Regression with robust standard errors            Number of obs =    2758
                                                   F(  2,  2755) =   28.95
                                                   Prob > F      =  0.0000
                                                   R-squared     =  0.0214
                                                   Root MSE      =  .51117
------------------------------------------------------------------------------
             |               Robust
      dlmfood |     Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dlincome |   .0386409   .0129605     2.98   0.003     .0132277    .0640541
   dmeanlinc |   .2258966   .0397903     5.68   0.000     .1478748    .3039184
       _cons |  -.0043645   .0126626    -0.34   0.730    -.0291936    .0204646
------------------------------------------------------------------------------

.  /*nonfood*/
> regress dlmnfood dlincome dmeanlinc $xvec1 , robust;
Regression with robust standard errors            Number of obs =    2762
                                                   F(  2,  2759) =   13.79
                                                   Prob > F      =  0.0000
                                                   R-squared     =  0.0112
                                                   Root MSE      =  .84619
------------------------------------------------------------------------------
             |               Robust
     dlmnfood |     Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dlincome |   .0752466   .0216662     3.47   0.001     .0327629    .1177303
   dmeanlinc |    .173113   .0650467     2.66   0.008     .0455678    .3006582
       _cons |   .0632033   .0200307     3.16   0.002     .0239267    .1024799
------------------------------------------------------------------------------

. *******4.  do instrumental variables estimates, with idiosyncratic shocks as
instruments for income;
. global xvec1="femhead headage headage2 dtmem";

. global shocks="llivedead illf2wk illm2wk";

. global ivar1="femhead headage headage2 dlnonfoody dtmem ";

.  /*instrumental variables estimates*/
> areg dlincome $ivar1 $shocks, absorb(unirnd);
                                                   Number of obs =    2664
                                                   F(  8,  2605) =   16.46
                                                   Prob > F      =  0.0000
                                                   R-squared     =  0.1322
                                                   Adj R-squared =  0.1129
                                                   Root MSE      =   .8213
------------------------------------------------------------------------------
    dlincome |     Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     femhead |   .1279064   .1170858     1.09   0.275    -.1016842    .3574971
     headage |  -.0024199   .0075698    -0.32   0.749    -.0172633    .0124235
    headage2 |   .0000104   .0000768     0.14   0.892    -.0001402    .0001611
  dlnonfoody |   .0796374   .0094153     8.46   0.000     .0611753    .0980995
```

```
        dtmem |  -.1253751   .0198886    -6.30   0.000    -.1643741   -.0863761
     llivedead |  -.0441487   .0114202    -3.87   0.000    -.0665423   -.0217552
        illf2wk |  -.0141088   .0091202    -1.55   0.122    -.0319923    .0037748
        illm2wk |   .0065925   .0104522     0.63   0.528    -.0139031     .027088
          _cons |  -.0889919   .1781498    -0.50   0.617    -.4383214    .2603376
------------+----------------------------------------------------------------
       unirnd |         F(50, 2605) =        5.349   0.000         (51 categories)

. test dlnonfoody llivedead illf2wk illm2wk;
 ( 1)  dlnonfoody = 0
 ( 2)  llivedead = 0
 ( 3)  illf2wk = 0
 ( 4)  illm2wk = 0
       F(  4,  2605) =   22.60
            Prob > F =    0.0000

. predict ehat, resid;
(1058 missing values generated)
. /*initial runs--change in consumption and change in income*/
> areg dlmcons dlincome $xvec1 $shocks ehat, absorb(unirnd) robust;

Regression with robust standard errors           Number of obs =     2662
                                                 F(  9,  2602) =     8.22
                                                 Prob > F      =   0.0000
                                                 R-squared     =   0.0944
                                                 Adj R-squared =   0.0738
                                                 Root MSE      =   .49401

------------------------------------------------------------------------------
              |               Robust
      dlmcons |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
     dlincome |   .2028674   .0735191     2.76   0.006     .0587056    .3470292
      femhead |   .1085395   .0853749     1.27   0.204      -.05887     .275949
      headage |   .0031943   .0047741     0.67   0.503    -.0061671    .0125556
     headage2 |   -.000034   .0000481    -0.71   0.480    -.0001283    .0000604
        dtmem |  -.1065248   .0211508    -5.04   0.000     -.147999   -.0650507
     llivedead |   .0090933   .0074413     1.22   0.222    -.0054981    .0236848
        illf2wk |    .002514   .0058653     0.43   0.668    -.0089871    .0140151
        illm2wk |   .0100917   .0067757     1.49   0.137    -.0031946    .0233781
          ehat |  -.1688371   .0750477    -2.25   0.025    -.3159964   -.0216778
          _cons |  -.0726597   .1125094    -0.65   0.518    -.2932768    .1479573
------------+----------------------------------------------------------------
       unirnd |  absorbed                                    (51 categories)

. /*disaggregate into food and nonfood; stick with 14 days illness?*/
> /*food expenditures*/
> areg dlmfood dlincome $xvec1 $shocks ehat , absorb(unirnd) robust;
Regression with robust standard errors           Number of obs =     2661
                                                 F(  9,  2601) =     8.28
                                                 Prob > F      =   0.0000
                                                 R-squared     =   0.1286
                                                 Adj R-squared =   0.1089
                                                 Root MSE      =   .47174

------------------------------------------------------------------------------
              |               Robust
      dlmfood |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
     dlincome |   .1364457   .0677066     2.02   0.044     .0036815    .2692099
```

```
    femhead |   .0114639   .0587097     0.20   0.845    -.1036584    .1265863
    headage |   .0029939   .0045917     0.65   0.514    -.0060099    .0119977
   headage2 |  -.0000336   .0000456    -0.74   0.461     -.000123    .0000558
      dtmem |  -.0982648   .0183497    -5.36   0.000    -.1342464   -.0622833
   llivedead |   .0108059   .0070751     1.53   0.127    -.0030676    .0246793
     illf2wk |    .000479   .0062588     0.08   0.939    -.0117936    .0127516
     illm2wk |   .0105774   .0065966     1.60   0.109    -.0023578    .0235125
       ehat |  -.1030242   .0689859    -1.49   0.135    -.2382969    .0322486
      _cons |   -.094305   .1101627    -0.86   0.392    -.3103205    .1217105
------------+----------------------------------------------------------------
     unirnd |  absorbed                                       (51 categories)

.                       /*nonfood*/
> areg dlmnfood dlincome $xvec1 $shocks ehat , absorb(unirnd) robust;
Regression with robust standard errors           Number of obs =     2664
                                                 F(  9,  2604) =     6.00
                                                 Prob > F      =   0.0000
                                                 R-squared     =   0.0794
                                                 Adj R-squared =   0.0585
                                                 Root MSE      =   .82883

------------------------------------------------------------------------------
            |              Robust
    dlmnfood |     Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
   dlincome |   .2888443   .1210579     2.39   0.017     .0514649    .5262238
    femhead |   .2160342   .1512615     1.43   0.153    -.0805708    .5126392
    headage |   .0022136    .007837     0.28   0.778    -.0131537     .017581
   headage2 |  -.0000213   .0000811    -0.26   0.793    -.0001803    .0001377
      dtmem |  -.1256248   .0305626    -4.11   0.000    -.1855543   -.0656953
   llivedead |   .0099354   .0143692     0.69   0.489    -.0182408    .0381116
     illf2wk |   .0043258   .0094626     0.46   0.648    -.0142292    .0228809
     illm2wk |   .0017717   .0111878     0.16   0.874    -.0201661    .0237094
       ehat |  -.2375459   .1233464    -1.93   0.054    -.4794128     .004321
      _cons |   .0102802   .1810817     0.06   0.955    -.3447984    .3653588
------------+----------------------------------------------------------------
     unirnd |  absorbed                                       (51 categories)

.                log close;
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. log cl
      log:  d:\vulnerability\toolkit\bangla.log
 log type:  text
 closed on:  21 May 2003, 14:57:59
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