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Measuring Vulnerability

The Director's Cut

Ethan Ligon* and Laura Schechter*

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Keywords: vulnerability, risk, Bulgaria,

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*University of California, Berkley, Department of Agricultural and Resource Economics.

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Measuring Vulnerability: The Director's Cut

Ethan Ligon and Laura Schechter *

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Abstract

Traditional poverty measures neglect several important dimensions of household welfare. In this paper we construct a measure of "vulnerability" which allows us to quantify the welfare loss associated with poverty as well as the loss associated with any of a variety of different sources of uncertainty. Applying our measure to a panel dataset from Bulgaria in 1994, we find that poverty and risk play roughly equal roles in reducing welfare. Aggregate shocks are more important than idiosyncratic sources of risk, but households headed by an employed, educated male are less vulnerable to aggregate shocks than are other households.

This is a longer, working-paper version of Ligon and Schechter (2003).

Economists have long used measures of poverty to summarize the well-being of less fortunate households in a population. Typically either income or consumption expenditures are measured over some relatively short period of time (e.g., a year), and these are regarded as some kind of proxy for the material well-being of the household. Policies are often explicitly crafted to reduce these poverty measures.

At the same time, economists have long recognized that a household's sense of well-being depends not just on its average income or expenditures, but on the risk it faces as well, particularly in households with fewer resources. To consider an extreme case, a household with very low expected consumption expenditures but with no chance of starving may well be poor, but they still might not wish to trade places with a household having a higher expected consumption but greater consumption risk. It seems desirable to have a measure of household welfare which takes into account both average expenditures as well as the risk households bear. Here we propose a simple definition of what we term *vulnerability*, and a simple technique for identifying vulnerable populations.

Our method may be contrasted with related efforts by several other authors, discussed at some length in Section 3. Several papers have sought to address the issue of risk and poverty by estimating expected values of the poverty indices introduced by Foster et al. (1984). However, while useful for measuring poverty, these indices have several perverse features when trying to measure the welfare consequences of risk, and a policymaker who

*Please direct correspondence to `ligon@are.berkeley.edu`. We thank Emmanuel Skoufias for providing the data used in the application of this paper, and UN/WIDER for supporting, in part, research on this theme.

sought to allocate resources to minimize the expected value of one of these indices would tend to assign too much risk to poorer households.

We proceed as follows. In Section 1, we define a utilitarian measure of vulnerability, and describe how it may be decomposed into distinct measures of poverty, aggregate risk, and idiosyncratic risk. In Section 2, we describe a method for estimating the vulnerability measure defined in Section 1, and show how our estimated measure is robust to measurement error in consumption expenditures, unlike measures proposed elsewhere; in Section 3 we relate these other attempts to measure vulnerability to our method.

We apply our techniques to a dataset from Bulgaria, described in Section 4. These data are of particular interest because the data are collected at monthly intervals, thus allowing us to characterize the importance of variations in household consumption at seasonal frequencies; further these were collected during a year in which there were large aggregate shocks associated with transition, allowing us to explore the extent to which different groups suffered the effects of a major restructuring of the Bulgarian economy, an exercise we undertake in Section 5. Section 6 concludes.

1 Defining Vulnerability

We take a utilitarian approach to defining vulnerability in a risky environment. Suppose there to be a finite population of households indexed by $i = 1, 2, \ldots, n$, and let $\omega \in \Omega$ denote the state of the world. We focus on the distribution of household i's consumption expenditures, $c^i(\omega)$, rather than measures of income or wealth on the grounds that these kinds of expenditures are what most directly determine household welfare. To measure vulnerability, for each household we first choose some strictly increasing, weakly concave function $U^i : \mathbb{R} \to \mathbb{R}$ mapping consumption expenditures into the real line. Given the function U^i, we define the vulnerability of the household by the function

$$V^i(c) = U^i(z) - \mathrm{E}U^i(c^i). \tag{1}$$

Here z is some certainty-equivalent consumption such that *if* household i had certain consumption greater than or equal to this number, we wouldn't regard the household as vulnerable. Thus, the choice of z is analogous to the choice of a "poverty line" in the literature on poverty measurement.

One way to motivate a particular choice of z is to explicitly measure *relative* vulnerability within the population. In this case, consider an allocation in which every household receives the expected *per capita* consumption bundle with certainty. Since there is no inequality, there can be no relative poverty; since there is no uncertainty there can be no risk. Thus, for this allocation one would want our measure of vulnerability to be equal to 0. This is accomplished simply by setting z equal to expected *per capita* consumption expenditures.

A second benefit of setting z equal to expected per capita consumption expenditures emerges if we also assume that households all have some common function U, so that $U^i(c) = U(c)$. In this case, while certain individual households (those with expected consumptions sufficiently greater than expected per capita consumption) may have a negative measure of vulnerability, the concavity of U insures (by Jensen's inequality) that the average vulnerability of the population is a non-negative number.

Taking expectations of an increasing, concave function of consumption expenditures has the effect of making vulnerablity depend not only on the mean of a household's consumption, but also on variation in consumption. Take, for example, the case in which consumption expenditures are bounded above by some b, and where we take $U^i(c) = -(c-b)^2$. In this case, differences in vulnerability between two households depend only on differences in the mean and variance of these households' consumption expenditures.

To better understand the balance between poverty and risk in our measure of vulnerability, note that we can decompose the measure into distinct components reflecting poverty and risk, respectively:

$$V^i(z) = [U^i(z) - U^i(\mathrm{E}c^i)] + [U^i(\mathrm{E}c^i) - \mathrm{E}U^i(c^i)]. \tag{2}$$

Note that the first bracketed term, which measures poverty, involves no random variables—it is simply the difference between a concave function evaluated at the "poverty line" and at household i's expected consumption expenditure. The concavity of U^i implies that as $\mathrm{E}c^i$ approaches the poverty line, an additional unit of expected consumption has diminishing marginal value in reducing poverty. For a suitable choice of $\{U^i\}$, it is easy to show that this poverty measure satisfies all the axiomatic requirements enumerated in Foster et al. (1984).

The second term of (2), which measures the risk faced by household i, is consistent with the ordinal measures of risk proposed by Rothschild and Stiglitz (1970) (though any monotone transformation would do as well). Further, this risk measure can can usefully be further decomposed into two distinct measures of risk, one aggregate, the other idiosyncratic. Let $\mathrm{E}(c^i|\bar{x})$ denote the expected value of consumption, c^i, conditional on knowledge of a vector of aggregate variables $\bar{x}$. Then we can rewrite the risk facing household i as

$$U^i(\mathrm{E}c^i) - \mathrm{E}U^i(c^i) = [U^i(\mathrm{E}c^i) - \mathrm{E}U^i(\mathrm{E}(c^i|\bar{x}))] + [\mathrm{E}U^i(\mathrm{E}(c^i|\bar{x})) - \mathrm{E}U^i(c^i)].$$

Here the first term expresses the *aggregate risk* facing the household, while the second filters out the aggregate component of risk to leave only the component of *idiosyncratic risk*. Putting it all together, we have

$$\begin{aligned} V^i(z) = \quad & [U^i(z) - U^i(\mathrm{E}c^i)] && \text{(Poverty)} \\ + \quad & [U^i(\mathrm{E}c^i) - \mathrm{E}U^i(\mathrm{E}(c^i|\bar{x}))] && \text{(Aggregate risk)} \\ + \quad & [\mathrm{E}U^i(\mathrm{E}(c^i|\bar{x})) - \mathrm{E}U^i(c^i)]. && \text{(Idiosyncratic risk)} \end{aligned}$$

Of course, the notation here is intentionally chosen to evoke comparisons with utility functions. If one were to adopt a utilitarian notion of welfare for some population of n households, then in principle one could choose a set of functions $\{U_i\}_{i=1}^n$ which match the indirect utility functions of this population. In this case, minimizing vulnerability is equivalent to maximizing the utilitarian social welfare function

$$\max_{\{c^i(\omega)\}} \sum_{i=1}^n \mathrm{E}U^i(c^i)$$

subject to some aggregate resource constraint.

Despite the notation, our proposed procedure of maximizing the sum of the expected values of concave functions of expenditures need not be interpreted as a utilitarian social welfare function. One of several possible alternative interpretations would have a paternalistic donor or NGO choose some concave function, with the shape of the function reflecting the *donor*'s preferences over the distribution and uncertainty of consumption expenditures. One happy consequence is that it is not necessary to be able to measure individual households' utility functions.

2 Estimating Vulnerability

Two additional steps are required before one can actually use data to compute a household's vulnerability. First, one must choose the functions $\{U^i\}$. Second, one must devise a way to estimate the conditional expectations which figure in our vulnerability measure. Here, we assume that that the $\{U^i\}$ take the simple form $U^i(c) = (c^{1-\gamma})/(1-\gamma)$ for some parameter $\gamma > 0$; as γ increases, the function U^i becomes increasingly sensitive to risk. We normalize c so that the average of consumption over all households in all periods equals 1.

Despite the apparently static nature of the vulnerability function defined above, to estimate risk we rely on variation over time. Accordingly, we denote the time t realization of household i's consumption expenditures as c_t^i, of household i's other idiosyncratic variables as x_t^i, and of the vector of aggregate variables by $\bar{x}_t$. We assume that $\mathrm{E}(c_t^i|\bar{x}_t, x_t^i) = \alpha^i + \eta_t + x_t^i\beta$, with $\theta = (\alpha^i, \eta_t, \beta')$ a vector of unknown parameters to be estimated.

In the presence of measurement error, using observed consumption to measure vulnerability as in Section 1 would lead the analyst to confute measurement error with idiosyncratic risk. To avoid this problem, we further decompose our measure of idiosyncratic risk into risk which can be attributed to variation in k observed time-varying household characteristics $x_t^i = (x_{1t}^i, \ldots, x_{kt}^i)$ and a risk which can neither be explained by these characteristics, nor aggregate variables, but which is due instead to variation in unobservables and to measurement error in consumption. Thus, rewriting the expression for vulnerability yields

$$\begin{aligned}
V^i &= [U^i(\mathrm{E}c) - \mathrm{E}U^i(\mathrm{E}c_t^i)] \qquad \text{(Poverty)} \\
&+ [U^i(\mathrm{E}c_t^i) - \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t))] \qquad \text{(Aggregate risk)} \\
&+ [\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t)) - \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_t^i))] \qquad \text{(Idiosyncratic risk)} \\
&+ [\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_t^i)) - \mathrm{E}U^i(c_t^i)]. \qquad \text{(Unexplained risk \& measurement error)}
\end{aligned}$$

We can further decompose "idiosyncratic risk" into k distinct sources. If the k variables x_{jt}^i are not mutually orthogonal they can first be orthogonalized via a Gram-Schmidt procedure. Once we have an orthogonal set of predictors, then we can write explained idiosyncratic risk simply as

$$
\begin{aligned}
\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t)) &- \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_t^i)) \\
&= [\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t)) - \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_{1t}^i))] \\
&+ [\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_{1t}^i)) - \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_{1t}^i, x_{2t}^i))] \\
&\vdots \\
&+ [\mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_{1t}^i, \ldots, x_{(k-1)t}^i)) - \mathrm{E}U^i(\mathrm{E}(c_t^i|\bar{x}_t, x_{1t}^i, \ldots, x_{kt}^i))].
\end{aligned} \tag{3}
$$

Of course, there is not generally a unique orthogonalization of the variables in x_t^i. Rather than relying on an arbitrary mechanical procedure to choose a particular orthogonalization (compare the related literature on principal components analysis, Muirhead (1982, e.g.,)), we choose a somewhat less arbitrary ordering of the elements of x_t^i, which determines the orthogonalization. Suppose, for example, that we have data on household income, and the number of pensioners and unemployed in the household. We would denote by x_{1t}^i the part of household income which is orthogonal to household and time effects; by x_{2t}^i the part of the number of pensioners in household i orthogonal to household effects, time effects, and household income, and by x_{3t}^i the part of the number of unemployed in household i orthogonal to all the other variables. Thus, using our example, the first bracketed term of (3) provides a measure of the welfare loss which can be predicted using variation in household i's income; the second bracketed term the change in prediction if we include data on number of pensioners, and so on.

We assume a stationary environment, and so we are led to estimate the unconditional expectation of household i's consumption by $\mathrm{E}c_t^i = \frac{1}{T}\sum_{t=1}^T c_t^i$. For the present application, we wish to choose θ so as to optimally predict c_t^i in a least-squares sense. In the presence of measurement error, choosing parameters to predict consumption has the consequence that our estimates of total risk will not be unbiased. However, given our assumptions on the measurement error process (ϵ_t^i), $\mathrm{E}(c_t^i|\bar{x}_t, x_t^i) = \mathrm{E}(\tilde{c}_t^i|\bar{x}_t, x_t^i)$, measurement error in consumption expenditures will influence only our measure of *unexplained* risk. This last measure will be incorrect by the difference

$$
\mathrm{E}U^i(\tilde{c}_t^i) - \mathrm{E}U^i(c_t^i),
$$

while our measures of aggregate and explained idiosyncratic risk will not be biased by this sort of measurement error.

Our parameterization of $\mathrm{E}(c_t^i|\bar{x}_t, x_t^i)$ suggests the linear estimating equation

$$
\tilde{c}_t^i = \alpha^i + \eta_t + x_t^i\beta + v_t^i, \tag{4}
$$

where the conditioning information $(\bar{x}_t, x_t^i)$ is understood to include the knowledge of the date and of the identity of the household,[1] where v_t^i is a disturbance term equal to the sum of both measurement error in consumption as well as prediction error, and where the household fixed effects α^i are restricted to sum to zero.

[1]Thus, $\{\eta_t\}$ captures the influence of changes in aggregates, and $\{\alpha^i\}$ captures the influence of fixed household characteristics on predicted household consumption.

3 Other Definitions

A number of papers have, in recent years, sought to define and measure something called "vulnerability." As our measure differs from these earlier efforts, we'll take a moment to relate our measure to the measures defined by others.[2] These other efforts fall into one of two groups. The first attempts to measure the *exposure* households have to risks observed by the econometrician; the second attempts to estimate *expected* values of traditional poverty measures. We discuss each group in turn.

3.1 Exposure to observed risks

This approach to the measurement of vulnerability (Amin et al. (1999); Glewwe and Hall (1998); Dercon and Krishnan (2000)) focuses on the response of households' consumption expenditures to various observable shocks, such as drought or idiosyncratic fluctuations in income. If household consumption expenditures covary with income shocks, then one may infer that a risk-averse household lacks the means to smooth or insure away these shocks to its expenditures. Note that this measure of vulnerability does not depend directly on a household's level of consumption. Neither does it depend directly on the risk a household bears—a household with large variation in consumption which does not stem from variation in observables would have a low measured vulnerability. Of course, this latter feature could be regarded as a virtue; the method seems useful for identifying particular sources of risk, which may then be an appropriate focus of policy.

Amin, Rai, and Topa (1999) Amin, Rai, and Topa (1999) use panel data from Bangladesh to try and identify households whose consumption tends to vary with income, after controlling for household fixed effects and aggregate variation in mean consumption. Accordingly, they estimate (in differences) a version of our prediction equation (4) with the idiosyncratic vector of variables x_t^i simply equal to household income,

$$\mathrm{E}(c^i|\bar{x}, x^i) = \alpha^i + \eta_t + x_t^i\beta^i. \tag{5}$$

Note the use of a household-specific coefficient β^i, which the authors call the estimated "vulnerability" of household i. This is meant to capture the reduction in welfare associated with the additional risk a household bears if its consumption co-moves with risky (or time-varying) income.[3] This measure is closely related to what we term "explained idiosyncratic risk" (and does not capture aggregate risk). To see this, suppose we treat idiosyncratic income (or rather that part of income orthogonal to household and time effects) as the first element of the vector x_t^i of idiosycratic variables. Then, using the Amin-Rai-Topa prediction equation (5), our expression for the idiosyncratic risk associated with income for household i (from (3)) is simply

$$\mathrm{E}U^i(\alpha^i + \eta_t) - \mathrm{E}U^i(\alpha^i + \eta_t + x_{1t}^i\beta^i).$$

[2]For an excellent overview of different means of quantifying vulnerability see Kamanou and Morduch (2001).

[3]The households whose consumptions are negatively correlated with income will have negative β^i, and are thus considered to have very low vulnerability.

While the relationship of our vulnerability measure to that of Amin, Rai, and Topa (1999) is thus made clear, our measure corrects an important defect of the Amin-Rai-Topa measure. In particular, β^i is simply equal to the covariance of idiosyncratic consumption with idiosyncratic income divided by the variance of idiosyncratic income. Accordingly, not only will Amin, Rai, and Topa (1999)'s measure not depend on levels of income or consumption; it will be *negatively* related to the variance of income. Thus, if two households have precisely the same consumption realizations in every state, but the second household has a more variable income stream, then Amin, Rai, and Topa (1999) would regard the second household as the less vulnerable. Consider now two households with the same measure of vulnerability. One household may face many income shocks, while the other may face much fewer. We would like to say that vulnerability is greater in the first case, but this measure would say they are the same. Thus, this measure is unsuitable for inter-household comparisons. One can remedy this defect by multiplying β^i by x^i_{1t}; this modified measure of vulnerability becomes a special case of ours if $U^i(c) = -(c-b)^2$ (where b is a "bliss point" parameter), if there is no inequality in expected consumptions, and if there is no aggregate or unexplained variation in household consumption.

Glewwe and Hall (1998) Glewwe and Hall (1998) and Glewwe and Hall (1995) measure something they call "vulnerability" in Peru, but in contrast to Amin, Rai, and Topa (1999), are particularly interested in the response of households' consumptions to *aggregate* shocks. In particular, Glewwe and Hall (1995) estimate (in differences) a version of our prediction equation (4) with the idiosyncratic vector of time-invariant household characteristics x^i, but with time-varying coefficients,

$$\mathrm{E}(c^i_t|\bar{x}, x^i) = \alpha^i + \eta_t + x^i\beta_t. \tag{6}$$

Contrast this with the prediction equation (5) of Amin, Rai, and Topa (1999). The key difference is that Glewwe and Hall focus on household level consumption responses to aggregate shocks (which they identify with β_t), while Amin, Rai, and Topa (1999) focus on household response to idiosyncratic shocks (which they identify with β^i).

Glewwe and Hall then take changes in the log of consumption as their measure of vulnerability.[4] Thus their vulnerability measure is

$$U^i(c^i_{t+1}) - U^i(c^i_t),$$

where $U^i(c) = \log(c)$. Because they look at changes in utility after a large negative macroeconomic shock, those households whose utility fell by less than average are considered less vulnerable. With more periods of data covering times of both positive and negative shocks, it would be difficult to know how to aggregate this measure over time. Since they weight downside risk as the negative of upside risk it would also make it seem as though a household with a continuously increasing consumption stream was less vulnerable than a household with a constant consumption stream.

[4] Cunningham and Maloney (2000) use a similar measure of vulnerability. Their measure of vulnerability is $(c^i_{t+1} - c^i_t)(\frac{U^{i\prime}(\overline{c_i})}{U^{i\prime}(\bar{\bar{c}})})$, which is approximately equal to Glewwe and Hall's measure when utility is logarithmic.

Dercon and Krishnan (2000) Dercon and Krishnan (2000) takes an approach similar to that of Amin, Rai, and Topa (1999) and Glewwe and Hall (1998), but estimates households' exposure to both idiosyncratic and village level shocks. The authors work with an estimating equation of the form

$$c_t^i = \alpha^i + \gamma S_t^i + \beta X_t^i + e_t^i$$

where X_t^i contains aggregate, time-varying variables such as wages and prices, and where S_t^i contains observed idiosyncratic shocks faced by individuals and households (e.g. animal disease, personal illness). Thus β is a measure of households' exposure to aggregate shocks, while γ is a measure of how vulnerable households are to assorted idiosyncratic shocks.

3.2 Expected poverty

Recall that Foster et al. (1984) define a family of poverty measures, P_α. A second approach to the measurement of vulnerability has been to adapt these standard poverty measures to a non-deterministic setting by estimating the *expected* value of P_α. Although methods for estimating these expected measures vary considerably, several papers share this approach to defining a measure of vulnerability. We divide these papers into two groups, depending on their favored choice of the parameter α, which governs the property of the poverty measure. Several authors have chosen to work with the headcount measure of poverty ($\alpha = 0$); others have chosen to work with the "squared poverty gap" ($\alpha = 2$). Each of these alternatives has differing strengths and weaknesses, and so we discuss each in turn below.

Expected headcount ($\alpha = 0$) A number of authors (Chaudhuri (2001); Chaudhuri et al. (2001); Christiaensen and Boisvert (2000); Pritchett et al. (2000)) use a measure of household vulnerability which is simply the expected headcount measure of poverty, or $\mathrm{E}P_0$ in the notation of Foster et al. (1984). This measure depends on poverty, aggregate risk, and idiosyncratic risk. This measure is simple and comprehensive—it varies with a households' wealth and aggregate and idiosyncratic sources of risk. However, the measure suffers some of the same shortcomings of the headcount measure of poverty, aggravated by issues related to the way in which it implicitly treats household risk attitudes. Consider a household whose present consumption is somewhat above the poverty line, but which receives a very bad shock with small probability. Consistent with this story, we can imagine that expected consumption for the household might lie slightly below the poverty line, despite the fact that the probability of the household falling into poverty was less than one half. This might not be so bad, except that if the household is risk averse, with von Neumann-Morgenstern utility, then it would *prefer* to consume its expected consumption with certainty. Thus, if offered the choice (say via the offer of actuarially fair insurance) the household would choose the consumption stream which would cause it to be 'vulnerable' according to this definition.[5] Thus, this definition of vulnerability could be used to motivate public policies (restricting insurance?) which would reduce welfare. Related, a policymaker could reduce this measure

[5] Similarly, a household which faces no risk, with constant consumption below the poverty line, could be made less 'vulnerable' by increasing the variability of its consumption (while holding the mean constant) if this increased the likelihood that its consumption would be above the poverty line.

of vulnerability by exposing poor households to very large risks—though some households would sink further into poverty, other more fortunate households might vault into the ranks of the non-poor. Policymakers using this measure implicitly assume that poor households are risk-seeking.

Expected squared poverty gap ($\alpha = 2$) Finally, we turn our attention to Kamanou and Morduch (2001) and Ravallion (1988). Ravallion doesn't use the term "vulnerability," preferring to think about "expected poverty" (Kamanou and Morduch (2001) look at expected changes in poverty). Thus, Ravallion's measure amounts to the expected value of a concave function of household consumption; basically his measure is a special case of the "risk" component of our measure of vulnerability (1). His focus is more on dynamics than it is on risk (he attempts to measure "persistent" and "transient poverty") rather than at risk *per se*; nonetheless, since we rely on time-series variation to identify risk, there are numerous points of similarity between his paper and ours.

With values of $\alpha > 1$, the Foster et al. (1984) poverty measure attributes risk-aversion to households. However, P_α still seems ill-suited to representing household risk attitudes. The first problem arises because these measures assign no weight to the welfare of households whose consumption is (perhaps only momentarily) greater than the poverty line. The second has to do with the nature of the risk preferences implicit in this measure—Foster, Greer and Thorbecke's poverty measure P_α 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 non-negative parameter. However, even if $\alpha > 1$ (so that households are risk-averse), this implies that households have increasing absolute risk aversion, which is sharply at odds with existing research on the risk preferences of poor households.

4 Data

The data we will use in this study is from the Household Budget Survey (HBS) in Bulgaria, collected by the Central Statistical Office of Bulgaria, and previously described by Peters and Hassan (1995) and Skoufias (2001). It includes information on 2287 households over 12 months. The data is taken from a random sample, but households with only one monthly observation or per capita consumption below the 1st percentile or above the 99th percentile have been dropped. The survey includes variables such as age, gender, education, sector of the economy, and employment status. Most importantly this survey contains detailed information on household level income and consumption.

This survey was taken during a very tumultuous period for Bulgaria. In 1991 price liberalization was undertaken and the share of administered prices in the Consumer Price Index went down from 70% to 24%, and by 1992 down even further to 16%. This price liberalization brought about severe output drops, perhaps caused by the disruption of productive links. The Gini Index between 1987 and 1989 was .23 and GDP per capita was 1730 Bulgarian Leva. Between 1993 and 1997 the Gini Index rose to 0.34 while per capita GDP fell to 1270 leva. In response to all of these changes, in 1994 the communists were reelected to power and the government increased the share of controlled prices to 43% (Roland (2000)). Using data from a period of such extreme shocks may make it possible to detect which households are insured against fluctuations.

A problem with most measures of consumption is that they do not reflect actual consumption when households consume out of their storage or their own production. This dataset avoids that problem. The HBS contains, for each food item, information on its stock at the beginning and end of each month, as well as flow quantities entering or leaving the household from production at home, gifts to or from friends, and quantities used as seed.[6] Skoufias has created a food consumption variable for each food item which he calculates as follows:

$$c_{it} = I_{it} + P_{it}Q_{it}$$

where he defines I_{it} as the value of purchases of that item and P_{it} as the national median unit value of that item. Q_{it} is the quantity in stock at the beginning of the month minus the quantity in stock at the end of the month, plus that obtained from reprocessing, from business organizations, from other sources, and produced at home. In addition he subtracts the quantity used for reprocessing or to feed animals, given out as presents or loans, sold, lost, wasted, or used for seed.

For non-food items it had not been possible to use the same approach.[7] The HBS survey contains no information on their stock, only on monthly expenditures and domestic production. Skoufias also created a measure of non-food expenditures from monthly purchases plus domestic production times the median unit value of that item. One can sum food and non-food consumption to find total consumption.

The data set contains equally detailed income data. The measure of income we use in our paper includes salary, self-employment income, rent, interest, dividends, pension, unemployment benefits, disability payments, child allowances, maternal benefits, family benefits, other benefits, farm product sales minus farm product expenses, property sales, and other income. We also have data on, but do not include, transfers from friends and relatives and net loans, borrowings, and savings. All consumption and income variables are normalized by the national CPI with a base of June 1994. We have also expressed these in units of adult equivalent consumption.[8]

5 Vulnerability in Bulgaria

Summary statistics for the variables included can be found in Table 1. Food consumption is negative in one month for 16 households, and total consumption is negative in one month for seven households. Those households have been excluded from the analysis. We see that

[6] Food items include cereals, meats, milk, fish, eggs, dairy products, fruits, vegetables, sugar, fats, beverages, alcohol, and expenditures on eating out.

[7] Non-food items include tobacco, electricity, central heating and other energy, trash, water, telecommunications, education, gasoline, transportation, furniture, health, clothing, entertainment and leisure, rent and home maintenance, insurance, cleaning, small appliances, domestic services, fees, and taxes.

[8] Our measure of adult equivalents assigns the consumption of adult males a weight of 1 and adult females a weight of 0.9 (adult means sixteen or older). Children aged 0 to 4 count as .32, aged 5 to 9 as .52 and ages 10 to 15 as .67. This is nearly the scheme used by Townsend (1994), save that our age brackets are slightly different.

Variable	Value
Monthly total cons. per capita (in Leva)	2787.2
Gini for total cons.	0.2601
Monthly food cons. per capita (in Leva)	1603.8
Gini for food cons.	0.2202
Monthly income per capita (in Leva)	2562.4
Gini for income	0.3087
# workers / family	1.052
# pensioners / family	0.234
# unemployed / family	0.893
Family Size	2.929
Age of hh head	54.6
Cultivate land	53.87 %
Land cultivated (in decares) by those who cultivate	2.40
No education	11.11 %
Primary education	34.94 %
Secondary education	41.23 %
Post-Secondary education	12.72 %
Male (hh head)	77.70 %
Own animals	43.90 %
City	63.75 %

Table 1: Summary Statistics

inequality is quite low, and that there seems to be a fair amount of unemployment. The sample includes both city and village dwellers. The annual average exchange rate for 1994 was 54.1 leva to the dollar, and in terms of purchasing power parity it was 14.8 leva to the dollar. This means that the average per-capita monthly income was approximately $47.36, or, in terms of PPP, $173.14.

We seek to estimate vulnerability in Bulgaria. We will also decompose vulnerability up into 8 distinct components. We will use as our function $U^i(c) = (c^{1-\gamma})/(1-\gamma)$. If we regard this as a utility function, then the parameter γ can be interpreted as the household's relative risk aversion. In rough keeping with estimates of this parameter found in the microeconometric literature, we take $\gamma = 2$. As discussed in Section 1, vulnerability can be divided into the part which comes from poverty, the part which comes from aggregate risk, the part which comes from idiosyncratic risk, and unexplained risk. Idiosyncratic risk can be divided even further to look at the contribution of changes in specific variables. We divide idiosyncratic risk into three parts: risk arising from variation in income stream, from changes in the number of pensioners in each household, and from the number of unemployed in each household.

Using the techniques described in Section 2, we estimate the contributions of each of the elements of vulnerability. It is interesting to compare the magnitudes of the 8 parts. We can calculate the percentage welfare loss due to each element of vulnerability.[9] We bootstrap confidence intervals for each of these components.

In Table 2 and Table 3 we decompose vulnerability for total consumption and food consumption respectively into poverty, aggregate risk, idiosyncratic risk, and unexplained risk. For both measures, poverty is the largest single component of vulnerability. After that, unexplained risk is the second largest component, and aggregate risk is the third largest component. Explained idiosyncratic risk is quite small, although the considerably larger unexplained risk may be made up of much idiosyncratic risk due to unobservable shocks.

We also look at the correlates of these elements of vulnerability. To do this we regress each element of vulnerability on a set of fixed household characteristics. For household characteristics which vary over the 12 month period, we use the mean value of that characteristic as our right hand side variable. We bootstrap standard errors for the coefficients. It is interesting to note that the correlates of vulnerability are extremely similar to the correlates of poverty. In addition, it is to be expected that the correlates of aggregate risk will be the same as the correlates of poverty. Aggregate shocks are, by definition, the same for all households, and so the poor households will experience greater impact on their utility from this component of risk.

We find that households with more educated heads are less vulnerable, with college educated heads being on average 37% less vulnerable than households with uneducated heads. Most of this reduction (33%) is due to educated households having higher expected consumption expenditures, but these highly educated households also face significantly less aggregate and idiosyncratic risk. Households which own animals or live in villages (as opposed to cities) are also less vulnerable, mostly because of their higher consumption. They also experience no more risk than more urban households. Given that one usually considers agriculture to be a more risky source of livelihood, it is interesting that these households experience no higher risk than other households. (On the other hand, decares of land cultivated has no sgnificant effect on vulnerability.) Perhaps this is because of unobserved mutual insurance mechanisms which are at work.

Households which have many pensioners or workers but smaller family size are less vulnerable. This means that having a family which includes more income earning members (pensioners and workers) decreases vulnerability. Families with more unemployed and children, on the other hand, are more vulnerable. Perhaps this is because of the greater number of non-income generating members in these households.[10] Those households with more pensioners or workers and smaller family size experience both higher levels of consumptions and lower levels of idiosyncratic risk in food consumption. These households experience more unexplained risk. Often, when increasing the number of employed members in a household, a household ends up facing more risk from unobservable sources. The gender of the household head has negligible effects on vulnerability, but reduces aggregate risk; this contrasts with the results of Glewwe and Hall (1998), who find that female headed households are no more or less vulnerable to aggregate sources of risk than are male headed households. Households

[9] As we have defined our utility function, the utility from perfect equality in a riskless society is equal to 1. Thus, the percentage welfare loss from vulnerability is equal to the size of vulnerability.

[10] In fact, most unemployed workers earn unemployment benefits, and some children generate income as well.

Average Value (in utils)	Vuln	Pov	Agg Risk	Idio Risk	Unexp Risk
	0.2637*** =	0.1404*** +	0.0281*** +	0.0023* +	0.0929***
	[0.2533 , 0.2743]	[0.1324 , 0.1488]	[0.0256 , 0.0311]	[0.0000 , 0.0047]	[0.0872 , 0.0986]
Variable	Coef	Coef	Coef	Coef	Coef
Primary Ed.	−0.0717**	−0.0726**	−0.0058	0.0009	0.0058
	(0.0321)	(0.0289)	(0.0042)	(0.0943)	(0.0947)
Secondary Ed.	−0.2356***	−0.2149***	−0.0212***	−0.0059	0.0064
	(0.0354)	(0.0316)	(0.0045)	(0.0288)	(0.0309)
Post-Sec. Ed.	−0.3350***	−0.3097***	−0.0262***	−0.0092	0.0101
	(0.0377)	(0.0340)	(0.0045)	(0.0237)	(0.0266)
Male	−0.0300	−0.0145	−0.0056*	−0.0016	−0.0083
	(0.0256)	(0.0229)	(0.0032)	(0.0140)	(0.0156)
Age	0.0083*	0.0076*	0.0014***	0.0011	−0.0018
	(0.0047)	(0.0039)	(0.0005)	(0.0109)	(0.0110)
Age Squared	−0.0000	−0.0000	−0.0000**	−0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Own Animal	−0.1001***	−0.0946***	−0.0093***	0.0123	−0.0086
	(0.0259)	(0.0233)	(0.0033)	(0.0231)	(0.0243)
Land Cultivated	−0.0011	−0.0009	0.0001	0.0001	−0.0004
	(0.0025)	(0.0023)	(0.0002)	(0.0011)	(0.0011)
Urban	0.0758***	0.0693***	0.0060*	−0.0069	0.0075
	(0.0262)	(0.0230)	(0.0032)	(0.1151)	(0.1154)
# of Pens.	−0.1183***	−0.0998***	−0.0177***	−0.0276	0.0267
	(0.0212)	(0.0191)	(0.0034)	(0.0413)	(0.0420)
# of Emp.	−0.3095***	−0.2826***	−0.0326***	−0.0372	0.0429
	(0.0237)	(0.0206)	(0.0044)	(0.1656)	(0.1658)
Fam. Size	0.2426***	0.2204***	0.0242***	0.0174*	−0.0195*
	(0.0137)	(0.0121)	(0.0030)	(0.0096)	(0.0112)

Table 2: Correlates and breakdown of vulnerability in total consumption. These regressions also include province dummies. Numbers in parenthesis are bootstrapped standard errors, and those in brackets are 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

Average Value (in utils)	Vuln	Pov	Agg Risk	Idio Risk	Unexp Risk
	19.7156*** =	10.7900*** +	2.6430*** +	0.1472*** +	6.1354***
	[18.9191 , 20.5250]	[10.1679 , 11.4264]	[2.4574 , 2.8578]	[0.0852 , 0.2210]	[5.7690 , 6.4939]
Variable	Coef	Coef	Coef	Coef	Coef
Primary Ed.	−4.3522	−5.0335**	−0.4169	−0.1722	1.2703
	(2.6999)	(2.3834)	(0.3009)	(0.2659)	(0.8333)
Secondary Ed.	−12.9181***	−12.1466***	−1.2685***	−0.6798**	1.1769
	(3.0069)	(2.6271)	(0.3225)	(0.2735)	(0.9419)
Post-Sec. Ed.	−16.4589***	−15.5674***	−1.3940***	−0.8678***	1.3703
	(3.4492)	(3.0623)	(0.3443)	(0.2642)	(0.9771)
Male	−3.3631	−2.0415	−0.7126**	−0.1312	−0.4778
	(2.4076)	(2.0156)	(0.2796)	(0.1092)	(0.5758)
Age	0.6755*	0.6554**	0.1454***	0.1295***	−0.2548
	(0.3872)	(0.3190)	(0.0362)	(0.0429)	(0.1576)
Age Squared	−0.0048	−0.0046	−0.0012***	−0.0011***	0.0021
	(0.0034)	(0.0029)	(0.0003)	(0.0003)	(0.0013)
Own Animal	−12.0656***	−12.0769***	−0.9161***	0.1859	0.7416
	(2.3172)	(1.9641)	(0.2524)	(0.1216)	(0.6960)
Land Cultivated	−0.0237	−0.0407	0.0088	0.0051	0.0032
	(0.1993)	(0.1801)	(0.0158)	(0.0063)	(0.0398)
Urban	8.6554***	7.3798***	0.5765**	−0.0694	0.7685
	(2.2916)	(1.8868)	(0.2292)	(0.1061)	(0.7627)
# of Pens.	−7.3809***	−5.7357***	−0.9527***	−1.1472***	0.4548
	(1.8089)	(1.5443)	(0.2373)	(0.3958)	(0.7261)
# of Emp.	−17.5215***	−15.3678***	−1.7694***	−2.0531***	1.6688*
	(1.9280)	(1.5413)	(0.2796)	(0.4834)	(0.9345)
Fam. Size	20.8202***	19.0939***	1.7719***	1.2708***	−1.3164**
	(1.1202)	(0.9319)	(0.1979)	(0.3609)	(0.6218)
R^2	0.3996	0.3509	0.4594	0.2694	0.2710

Table 3: Correlates and breakdown of vulnerability in food consumption. These regressions also include province dummies. Numbers in parenthesis are bootstrapped standard errors, and those in brackets are 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

	Pov	Agg Risk	Idio Risk	Unexp Risk
Pov	1.00^{***}	1.00^{***}	-0.08^{**}	0.04
	—	[1.00,1.00]	[-0.13,-0.02]	[-0.01,0.08]
Agg Risk	0.84^{***}	1.00^{***}	-0.08^{**}	0.04
	[0.82,0.85]	—	[-0.13,-0.02]	[-0.01,0.08]
Idio Risk	0.11	0.25^{**}	1.00^{***}	-0.34^{***}
	[-0.02,0.22]	[0.03,0.42]	—	[-0.40,-0.28]
Unexp Risk	-0.07	-0.20^{**}	-0.36^{***}	1.00^{***}
	[-0.16,0.02]	[-0.33,-0.06]	[-0.69,-0.22]	—

Table 4: Pearson correlations between elements of vulnerability in total consumption below the diagonal and Spearman rank correlations above the diagonal. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

	Pov	Agg Risk	Idio Risk	Unexp Risk
Pov	1.00^{***}	1.00^{***}	-0.05	0.25^{***}
	—	[1.00,1.00]	[-0.13,0.03]	[0.20,0.29]
Agg Risk	0.86^{***}	1.00^{***}	-0.05	0.25^{***}
	[0.85,0.88]	—	[-0.13,0.03]	[0.20,0.29]
Idio Risk	0.29^{***}	0.41^{**}	1.00^{***}	-0.14^{***}
	[0.18,0.39]	[0.16,0.59]	—	[-0.19,-0.09]
Unexp Risk	0.06	-0.01	-0.16	1.00^{***}
	[-0.04,0.14]	[-0.18,0.10]	[-0.42,0.02]	—

Table 5: Pearson correlations between elements of vulnerability in food consumption below the diagonal and Spearman rank correlations above the diagonal. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

with older household heads are also more vulnerable than those with younger heads.

In Table 4 and Table 5 we look at how each component of vulnerability is related to each other. The numbers below the diagonal are Pearson correlation coefficients and the numbers above the diagonal are Spearman rank correlation coefficients. (The numbers in parenthesis are bootstrapped 90% confidence intervals.) Poverty and aggregate risk have the exact same rank-order over households. This is by construction, as decreasing marginal utility implies that the poor will be most effected by aggregate shocks, which we have added into expected consumption uniformly over all households. Idiosyncratic risk and unexplained risk are significantly negatively correlated, perhaps because those households experiencing idiosyncratic risk are those for whom we observe the source of their vulnerability, while we do not observe the (different) source of vulnerability for those experiencing unexplained risk. Poverty and idiosyncratic risk are positively correlated for food consumption, but negatively correlated for total consumption. This may be because wealthier households are able to keep their food consumption smooth, while their total consumption may be more variable due to the inclusion of some durables.

In Table 6 and Table 7 we find the breakdown of the components of idiosyncratic risk and its correlates. Risk of unemployment is the largest component of idiosyncratic risk. This is especially interesting because we have already taken account of income risk, so that the effect of becoming unemployed is much larger than the simple effect it has on a household's income.

More educated households experience both less income risk, and less unemployment risk. It is extremely interesting to note that the reason the elderly are more susceptible to idiosyncratic risk in food consumption comes entirely from their increased unemployment risk. This was a period when many worker were being laid off, and the elderly had an especially difficult time coping with this. Households with animals experience more income risk in food consumption. (Perhaps this is because their income and food consumption both rise when they slaughter an animal.) Households with more pensioners or more workers experience less risk from unemployment and less income risk. Bigger households are more susceptible to both. This means that households with more unemployed and more children are the most unable to shield their food consumption from changes in income and unemployment status.

In Table 8 and Table 9 we look at the correlation between the different elements of idiosyncratic risk. Households which are more vulnerable to income risk are also more vulnerable to risk from a change in unemployment status. It is precisely those households which cannot shield their consumption from income risk which also cannot shield their consumption from unemployment risk.

Average Value (in utils)	Idio Risk 0.0023* = [0.0000 , 0.0047]	I.Risk Inc 0.0001 + [-0.0018 , 0.0021]	I.Risk Pens 0.0006* + [0.0001 , 0.0019]	I.Risk Unemp 0.0016* [0.0001 , 0.0030]
Variable	Coef	Coef	Coef	Coef
Primary Ed.	0.0009	0.0002	0.0011	−0.0004
	(0.0943)	(0.1286)	(0.1340)	(0.1016)
Secondary Ed.	−0.0059	−0.0013	−0.0004	−0.0042
	(0.0288)	(0.0631)	(0.0723)	(0.0464)
Post-Sec. Ed.	−0.0092	−0.0044	−0.0010	−0.0038
	(0.0237)	(0.0502)	(0.0540)	(0.0316)
Male	−0.0016	−0.0001	−0.0004	−0.0011
	(0.0140)	(0.0071)	(0.0098)	(0.0155)
Age	0.0011	−0.0004	0.0002	0.0013
	(0.0109)	(0.0107)	(0.0114)	(0.0116)
Age Squared	−0.0000	0.0000	−0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Own Animal	0.0123	0.0130	−0.0003	−0.0005
	(0.0231)	(0.0292)	(0.0308)	(0.0252)
Land Cultivated	0.0001	0.0001	−0.0000	0.0000
	(0.0011)	(0.0017)	(0.0020)	(0.0015)
Urban	−0.0069	−0.0070	0.0001	0.0001
	(0.1151)	(0.1375)	(0.1461)	(0.1256)
# of Pens.	−0.0276	−0.0067	−0.0095	−0.0114
	(0.0413)	(0.0542)	(0.0556)	(0.0430)
# of Emp.	−0.0372	−0.0159	−0.0043	−0.0169
	(0.1656)	(0.1649)	(0.1769)	(0.1779)
Fam. Size	0.0174*	0.0029	0.0027	0.0118
	(0.0096)	(0.0151)	(0.0164)	(0.0118)

Table 6: Correlates and breakdown of idiosyncratic risk in total consumption. These regressions also include province dummies. Numbers in parenthesis are bootstrapped standard errors, and those in brackets are 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

Average Value (in utils)	Idio Risk	I.Risk Inc	I.Risk Pens	I.Risk Unemp
	0.0055^{***} =	0.0014^{***} +	-0.0002 +	0.0043^{***}
	[0.0027 , 0.0093]	[0.0006 , 0.0023]	[-0.0005 , 0.0001]	[0.0016 , 0.0079]
Variable	Coef	Coef	Coef	Coef
Primary Ed.	-0.0097	-0.0016	-0.0005	-0.0077
	(0.0134)	(0.0016)	(0.0006)	(0.0132)
Secondary Ed.	-0.0233^{*}	-0.0055^{***}	-0.0001	-0.0177
	(0.0133)	(0.0020)	(0.0005)	(0.0131)
Post-Sec. Ed.	-0.0248^{**}	-0.0078^{***}	-0.0001	-0.0170
	(0.0121)	(0.0023)	(0.0005)	(0.0118)
Male	-0.0036	-0.0012	-0.0001	-0.0023
	(0.0039)	(0.0012)	(0.0002)	(0.0037)
Age	0.0042^{**}	0.0003^{*}	-0.0001	0.0039^{**}
	(0.0020)	(0.0002)	(0.0001)	(0.0019)
Age Squared	-0.0000^{**}	-0.0000^{*}	0.0000	-0.0000^{**}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Own Animal	-0.0026	0.0022^{*}	0.0000	-0.0049
	(0.0044)	(0.0013)	(0.0002)	(0.0042)
Land Cultivated	0.0001	0.0000	0.0000	0.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0002)
Urban	-0.0003	0.0004	-0.0001	-0.0005
	(0.0040)	(0.0012)	(0.0002)	(0.0038)
# of Pens.	-0.0390^{**}	-0.0060^{***}	0.0028	-0.0358^{**}
	(0.0186)	(0.0016)	(0.0027)	(0.0181)
# of Emp.	-0.0587^{**}	-0.0124^{***}	0.0012	-0.0476^{**}
	(0.0230)	(0.0029)	(0.0012)	(0.0226)
Fam. Size	0.0398^{**}	0.0061^{***}	-0.0007	0.0344^{*}
	(0.0180)	(0.0016)	(0.0007)	(0.0177)

Table 7: Correlates and breakdown of idiosyncratic risk in food consumption. These regressions also include province dummies. Numbers in parenthesis are bootstrapped standard errors, and those in brackets are 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

	I.Risk Inc	I.Risk Pens	I.Risk Unemp
I.Risk Inc	1.00^{***}	-0.16^{***}	0.23^{***}
	—	[-0.20,-0.12]	[0.20,0.27]
I.Risk Pens	0.08	1.00^{***}	-0.03
	[-0.88,0.64]	—	[-0.06,0.01]
I.Risk Unemp	0.08	0.33	1.00^{***}
	[-0.48,0.64]	[-0.93,0.48]	—

Table 8: Pearson correlation between elements of idiosyncratic risk in total consumption below the diagonal and Spearman rank correlations above the diagonal. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

	I.Risk Inc	I.Risk Pens	I.Risk Unemp
I.Risk Inc	1.00^{***}	0.22	0.16^{***}
	—	[-0.23,0.26]	[0.11,0.20]
I.Risk Pens	-0.11	1.00^{***}	-0.02
	[-0.34,0.23]	—	[-0.05,0.03]
I.Risk Unemp	0.35^{**}	-0.41	1.00^{***}
	[0.15,0.55]	[-0.57,0.47]	—

Table 9: Pearson correlation between elements of idiosyncratic risk in food consumption below the diagonal and Spearman rank correlations above the diagonal. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

<table>
<tr><td colspan="6">Vulnerability
0.2637***
[0.2533, 0.2743]</td></tr>
<tr><td>Poverty
0.5326***
[0.5173, 0.5477]</td><td colspan="5">Risk
0.4674***
[0.4523, 0.4827]</td></tr>
<tr><td></td><td>Aggregate Risk
0.2276***
[0.2074, 0.2526]</td><td colspan="3">Idiosyncratic Risk
0.0184*
[0.0001, 0.0382]</td><td>Unexplained Risk
0.7540***
[0.7209, 0.7831]</td></tr>
<tr><td></td><td></td><td>I.Risk Inc
0.0340
[−2.4657, 0.8598]</td><td>I.Risk Pens
0.2609
[−0.7409, 1.2690]</td><td>I.Risk Unemp
0.7051
[−0.0418, 2.5557]</td><td></td></tr>
</table>

Table 10: Share of utility lost due to each element of vulnerability in total consumption. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

<table>
<tr><td colspan="6">Vulnerability
0.3977***
[0.3669, 0.4326]</td></tr>
<tr><td>Poverty
0.4579***
[0.4245, 0.4900]</td><td colspan="5">Risk
0.5421***
[0.5100, 0.5755]</td></tr>
<tr><td></td><td>Aggregate Risk
0.3016***
[0.2591, 0.3513]</td><td colspan="3">Idiosyncratic Risk
0.0257***
[0.0123, 0.0435]</td><td>Unexplained Risk
0.6727***
[0.6144, 0.7211]</td></tr>
<tr><td></td><td></td><td>I.Risk Inc
0.2497***
[0.1135, 0.4848]</td><td>I.Risk Pens
−0.0309
[−0.1038, 0.0183]</td><td>I.Risk Unemp
0.7812***
[0.5352, 0.9364]</td><td></td></tr>
</table>

Table 11: Share of utility lost due to each element of vulnerability in food consumption. Numbers in brackets are bootstrapped 90% confidence intervals. ***- significant at the 1% level, **- significant at the 5% level, *- significant at the 10% level

In Table 10 and Table 11 we summarize these results and look at the share of utility lost due to each of the components of vulnerability. We see that vulnerability in total consumption causes an average utility loss of 26% and in food consumption causes a utility loss of 20%.[11] Just over half of this is due to poverty and just under half of this is due to risk. Over two thirds of risk is due to unexplained factors. Close to one third is due to aggregate risk, and a small share is due to observed components of idiosyncratic risk. Within idiosyncratic risk, over two thirds is due to risk of unemployment, while the rest is made up of income and pension risk. It would be interesting to know information about the idiosyncratic shocks households face to decompose our measure of unexplained risk even further.

We can also calculate the compensation which would be necessary to compensate people for their vulnerability. To compensate households for all vulnerability in total consumption would cost an average of 555 leva per person per month. For vulnerability in food conssumption it would cost an average of 243 leva per person per month. This compensation for vulnerability in total consumption can be broken down to 305 leva to compensate for poverty, 37 leva for aggregate risk, 3 leva for idiosyncratic risk, and 211 leva for unexplained risk. The compensation for vulnerability in food consumption can be broken down to 142 leva for poverty, 24 leva for aggregate risk, 0.2 leva for idiosyncratic risk, and 78 leva for unexplained risk.

6 Conclusion

In this paper we propose a simple measure of vulnerability. This measure is simply the difference between the utility a household would derive from consuming some particular bundle with certainty and the household's expected utility of consumption. This measure can be naturally decomposed into distinct measures of poverty, exposure to aggregate risk, exposure to idiosyncratic risk, and unexplained risk plus measurement error. Notably, our measures are robust to measurement error in the data used to estimate vulnerability, whether the error is in consumption expenditures or other 'explanatory' variables.

Of particular note is that by adopting a utilitarian framework we correctly capture the effects of risk on household welfare. This contrasts with some other measures of vulnerability, which work with the expected value of one of the Foster-Greer-Thorbecke poverty measures. Use of such measures as a guide to policy would tend to underestimate the value of mechanisms for reducing risk, such as credit, savings, or insurance.

Using data from Bulgaria we estimate this vulnerability measure, and its components, and also look at the correlates of each of the components of vulnerability. Our estimates suggest that in the elimination of poverty would increase welfare by 14% in our Bulgarian sample, while eliminating aggregate risk would increase welfare by nearly 3%. Idiosyncratic risk stemming from observable sources (income shocks, unemployment incidence, pensions), while significant, is unimportant in terms of magnitude.

Education is the most useful way to reduce vulnerability; households with college edu-

[11] This is an average over some utility losses and some utility gains from what people's utility would be in a world of absolute equality with no risk.

cated heads were significantly less poor, and significantly less vulnerable to both aggregate and idiosyncratic sources of risk. City dwellers can expect to be somewhat more poor, and for aggregate sources of risk to impact their food consumption more than is the case for their country cousins. Having pensioners or employed workers in one's household helps to reduce poverty, exposure to aggregate risk, and the impact of idiosyncratic risk on food consumption; on the other hand, one would not want to adopt a pensioner, as having an additional family member would increase vulnerability in each of these components by more than the adoptees pension status would reduce it.

We close by discussing two possible avenues for futher research. The framework we've adopted here adds uncertainty in a satisfactory way, by thinking of the functions $U^i(c)$ as an *ex post* indirect utility function. To permit a dynamic analysis, it's straightforward to think about instead regarding this function as the value function defined by Bellman's equation (with current consumption expenditures a function of asset holdings). However, we use time series variation in households' outcomes to identify the risk that they face. This makes it much more difficult to simultaneously think about extending our measure to permit any sort of dynamic analysis; doing so would require the structure of a proper dynamic model.

A second avenue is, perhaps, more immediately practical. As just noted, our present work requires panel data on households to estimate the vulnerability of those households. Such data are, of course, both expensive and time-consuming to collect. Faced with similar problems in poverty applications, other authors have tried to make inferences drawn from panel data to larger populations for whom only cross-sectional data exist, by matching households in the two samples on observables. A similar procedure seems feasible here.

University of California, Berkeley

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