Vulnerability as a Measure of Chronic Poverty

Laura Schechter
AAE, UW Madison

Questions

What is a ‘good’ measure of chronic poverty?

How can we switch from traditionally backward-looking measures, to more forward-looking measures.

Motivation

Chronic Poverty - expenditures at more than one point in time are important for hh well-being. Focusing on static poverty ignores much important information.

When looking at outcomes over time, both risk and poverty play important roles – “vulnerability” (World Development Report 2000/01).

Measurement depends on estimating the distribution of future consumption expenditures. But, it is hard to predict the future!

Elbers & Gunning (2006) is (arguably) the most serious effort thusfar at predicting the future for use in measures of hh well-being.

Results

Discuss four ways to make measures more forward-looking.

Can divide the population into those who are vulnerable due to raw poverty, those who face risk-induced vulnerability, and those who are not vulnerable.

Predicting future consumption leads to higher levels of risk, but that risk is less predictable.

Risk in South Africa is large relative to risk in other countries.

Idiosyncratic risk is largest due to income risk and changes in household size (AIDS?). Asset risk is negligible.

Outline of Talk

1. Traditional Vulnerability Estimation
2. Application to South Africa
3. Four Ways to Be Forward-Looking
4. Application to South Africa
5. Conclusions

Vulnerability Measure

Utilitarian approach to defining a measure of vulnerability.

Ligon and Schechter (2003): $V = U(z) - \mathrm{E}U(c^i)$.

Can be broken down into chronic poverty and chronic risk $V = [U(z) - U(\mathrm{E}c^i)] + [U(\mathrm{E}c^i) - \mathrm{E}U(c^i)]$. Poverty and risk satisfy axioms of Foster et. al. (1984) and Rothschild & Stiglitz (1970).

Normalize expenditures so $z = 1$.

Further Decomposition

Can further decompose risk into aggregate and idiosyncratic risk.

Let $\mathrm{E}(c^i|\bar{x})$ denote the expected value c^i conditioned on knowledge of aggregate outcomes $\bar{x}$. Then

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

The first term is the *aggregate risk* facing the household, while the second is *idiosyncratic risk*.

Even Further Decomposition

Decompose idiosyncratic risk into risk which can be attributed to variation in observed household characteristics x_t^i and a risk which can't be explained by such variation.

$$
\begin{aligned}
R^i = \quad & [U(\mathrm{E}c_t^i) - \mathrm{E}U(\mathrm{E}(c_t^i|\bar{x}_t))] && \text{(Aggregate)} \\
+ \quad & [\mathrm{E}U(\mathrm{E}(c_t^i|\bar{x}_t)) - \mathrm{E}U(\mathrm{E}(c_t^i|\bar{x}_t, x_t^i))] && \text{(Idiosyncratic)} \\
+ \quad & [\mathrm{E}U(\mathrm{E}(c_t^i|\bar{x}_t, x_t^i)) - \mathrm{E}U(c_t^i)]. && \text{(Unexplained)}
\end{aligned}
$$

Traditional Consumption Prediction

With data on T time periods, the distribution of observed consumption for each household is used as the distribution of potential consumptions for that household.

Useful when measurement error in consumption. Total vulnerability gives upper bound on vulnerability.

Use a prediction equation to predict consumption in each period. The explained part of the consumption distribution $(\hat{\mathrm{E}}(c_t^i|\bar{x}_t, x_t^i))$ (total vulnerability minus unexplained risk) gives you a lower bound on vulnerability.

Estimation

Need a way to estimate the conditional expectations in our risk measure.

We assume that $\mathrm{E}(\ln c_t^i | \bar{x}_t, x_t^i) = \alpha^i + \eta_t + x_t^i \beta$.

Optimally predict c_t^i in a least-squares sense.

We also assume CRRA utility: $U(c) = (c^{1-\gamma} - 1)/(1 - \gamma)$ and $\gamma = 2$.

South African KIDS Data

Panel data from 1993, 1998, 2004 in KwaZulu-Natal Province.

701 households in all rounds of data.

Carter & Maluccio (2003) suggest exposure to risk may be relatively high in South Africa. Period of dramatic political, social, and economic change.

Determinants of Vulnerability

	Vulnerability =	Poverty +	Risk
	0.219** =	0.0640** +	0.155**
	(1)	(2)	(3)
HH Size in 93	0.0784**	0.0715**	0.00688**
	(0.005)	(0.005)	(0.001)
Assets in 93	-3.73e-06*	-3.20e-06*	-5.29e-07*
	(1.70e-06)	(1.52e-06)	(2.55e-07)
Unearned Inc in 93	-0.000140**	-0.000123**	-1.67e-05
	(3.92e-05)	(3.39e-05)	(9.43e-06)
Educ Labor in 93	-0.136**	-0.122**	-0.0141**
	(0.010)	(0.009)	(0.002)
Indian	-0.540**	-0.458**	-0.0816**
	(0.031)	(0.027)	(0.007)
Pop Density > 500	-0.254**	-0.226**	-0.0279**
	(0.034)	(0.030)	(0.007)

First Breakdown

	Risk =	Agg Risk +	Idio Risk+	Unexp Risk
	0.155** =	0.0076** +	0.0332** +	0.1140**
	(1)	(2)	(3)	(4)
HH Size in 93	0.00688**	0.000442**	0.00307**	0.00337**
	(0.001)	(0.0001)	(0.001)	(0.001)
Assets in 93	-5.29e-07*	-1.99e-08*	-1.37e-07	-3.72e-07
	(2.55e-07)	(1.01e-08)	(7.82e-08)	(2.16e-07)
Unearned Inc in 93	-1.67e-05	-7.10e-07**	-2.20e-07	-1.58e-05*
	(9.43e-06)	(2.76e-07)	(3.95e-06)	(7.65e-06)
Educ Labor in 93	-0.0141**	-0.000756**	-0.00280**	-0.0105**
	(0.002)	(0.0002)	(0.001)	(0.002)
Indian	-0.0816**	-0.00366**	-0.0160**	-0.0619**
	(0.007)	(0.001)	(0.003)	(0.006)
Pop Density > 500	-0.0279**	-0.00133**	-0.00720**	-0.0194**
	(0.007)	(0.0004)	(0.002)	(0.006)

Second Breakdown

	Risk from Changes in...						
	Id Risk =	Assets +	Income +	Sick +	HhSize +	Uneduc +	Victim
	0.033^{**} =	7.11e-05 +	0.019^{**}+	1.53e-06 +	0.013^{**} +	7.47e-05 +	0.001
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HH Size	0.0031**	-1.38e-06	0.0009**	6.56e-07	0.0022**	-8.87e-05	9.28e-05
	(0.0006)	(1.44e-05)	(0.0002)	(2.44e-05)	(0.0005)	(7.01e-05)	(6.79e-05)
Assets	-1.37e-07	3.74e-09	-4.86e-08	1.25e-10	-9.42e-08	-3.93e-09	5.58e-09
	(7.82e-08)	(1.27e-08)	(4.07e-08)	(4.27e-09)	(6.27e-08)	(9.17e-09)	(1.61e-08)
Unearned Inc	-2.20e-07	-5.94e-08	-5.25e-06**	-1.47e-09	4.65e-06	1.97e-07	2.39e-07
	(3.95e-06)	(1.11e-07)	(1.49e-06)	(1.03e-07)	(3.43e-06)	(2.87e-07)	(3.33e-07)
Edu Labor	-0.0028**	2.32e-05	-0.0014*	-2.02e-06	-0.0016**	0.0002	-1.63e-05
	(0.0007)	(5.45e-05)	(0.0006)	(5.21e-05)	(0.0006)	(0.0001)	(0.0001)
Indian	-0.0160**	-7.36e-05	-0.0121**	1.18e-06	-0.0036*	-7.34e-05	-0.0002
	(0.003)	(0.0001)	(0.002)	(9.85e-05)	(0.002)	(0.0003)	(0.0003)
Pop Dens	-0.0072**	-4.51e-05	-0.0035*	-3.71e-06	-0.0032*	-0.0003	-9.35e-05
	(0.002)	(8.75e-05)	(0.002)	(0.0001)	(0.001)	(0.0003)	(0.0003)

Comparison

Risk is 71% of vulnerability. Compare to 46% in Bulgaria (monthly data) and 51% in Vietnam (yearly data).

Unexplained risk is 74% of total risk. Compare to 85% in Bulgaria and 79% in Vietnam.

In South Africa, vuln is .219, risk is .155 (agg is .008, idio is .033, unexp is .114).

In Bulgaria, vuln is .185, risk is .086 (agg is .011, idio is .002, unexp is .073).

In Vietnam, vuln is .165, risk is .085 (agg is .014, idio is .004, unexp is .067).

Forward Looking Measures

Thusfar measure has been backward-looking: use info on what happened to a household in the past, not what could happen in the future.

But how to predict the future? Will discuss four possible ways to do this, and carry out one with the data.

1: Modeling the Evolution of Shocks

Two hhs with equal prob of robbery. One is and one is not robbed in the survey years. For the first, poverty and risk will be overestimated while for the second they will be underestimated.

Estimate the probability that each household will experience any given shock (x_t^i). Then use this to re-estimate poverty and risk.

But, we know very little about why shocks occur, difficult to model. We may observe 25% of households experience robbery each year. We might assume every household has a 25% chance. But, maybe hhs w/out guns get victimized, and we don't know gun ownership.

And, idio risk is only 15% of vulnerability.

2: Explaining the Error Term

52% of vuln is unexp risk. Capture future vuln by modeling the heteroskedasticity in the error.

$$\hat{V} = U(z) - \int U(\hat{c}^i e^{\hat{\sigma}_\nu (z^i)\epsilon}) d\Phi(\epsilon)$$

Estimate using FGLS. (Chaudhuri, 2001)

Estimate the distribution of all possible outcomes which the household could face and calculate a more forward-looking measure of vulnerability in this manner.

Relatively simple, but disadvantage: impossible to separate out measurement error.

3: Assuming Difference Stationarity

Thusfar assumed consumption follows a stationary process. A weaker assumption could be changes in consumption are stationary and mean zero over time (consumption follows a random walk).

Change the estimating equation to: $\ln c_t^i = \ln c_{t-1}^i + \eta_t + x_t^i\beta + v_t^i$.

With three periods of data, could conduct a test for stationarity.

But, slightly problematic. One must do better at predicting future aggregate shocks (η_t) and unobserved shocks (v_t^i), since affect consumption today *and* consumption forever after.

4: Abandoning Stationarity

Estimating a dynamic model could improve predictions, but it requires specification and estimation of the model.

Elbers & Gunning (2006): capital stock and consumption level have steady state level depending on the hhs level of productivity. $V = \mathrm{E}_0 \sum_{t=1}^{T} \beta^{t-1}[U(z) - U(c_t^i)]$.

Highly dependent on assumptions. They assume a simple Ramsey growth model. But if actually asset-based poverty traps, then misestimate vulnerability.

Given the difficulties in correctly modeling the consumption generating process using economic theory, perhaps econometric techniques may be more appropriate here.

Focus on Explaining the Error

Heteroskedasticity in the error with a general form. Varies with urban, Indian, assets, assets squared, income, and income squared.

$v_t^{i2} = z^i \kappa + u_t^i$: used by Chaudhuri (2001), can lead to negative predictions.

$\log(v_t^{i2}) = z^i \kappa + u_t^i$: can lead to extremely high predictions.

Suggestion by Elbers, Lanjouw, and Lanjouw (2003) to predict consumption for poverty maps. $v_t^i = \xi_g + \epsilon_t^i$, mean of error differs across groups (rural African, rural Indian, urban African, and urban Indian). Then variance of ϵ is logistic: $\sigma^2 = [(Ae^{z^i \kappa})/(1 + e^{z^i \kappa})]$. Estimated using $\log[\epsilon_t^{i2}/(A - \epsilon_t^{i2})] = z^i \kappa + u_t^i$ where $A = 1.05 \max \epsilon_t^{i2}$.

FGLS

With heteroskedasticity OLS is inefficient.

Use two-step feasible generalized least squares (FGLS) for increased efficiency.

1. Get errors from OLS consumption prediction regression to estimate heteroskedasticity and get the variance/covariance matrix (Ω).

2. Use the new variance/covariance matrix to reestimate the coefficients in the original consumption prediction equation ($\hat{\beta} = (X'\Omega X)^{-1}(X'\Omega C)$).

Predicting Future Consumption

FGLS does not change total vulnerability, only the breakdown between the different pieces (since estimate of $\mathrm{E}U(c^i)$ based on observed outcomes for c^i).

Predict future outcomes of c^i, not just use observed outcomes for c^i.

Estimate expected consumption as $\mathrm{E}[\ln c^i | i] = \alpha^i$ and the variance of log consumption as above.

Results - not a whole lot changes!

Equations

$$\ln c^i \sim N(\mu^i, \sigma^2(z^i))$$

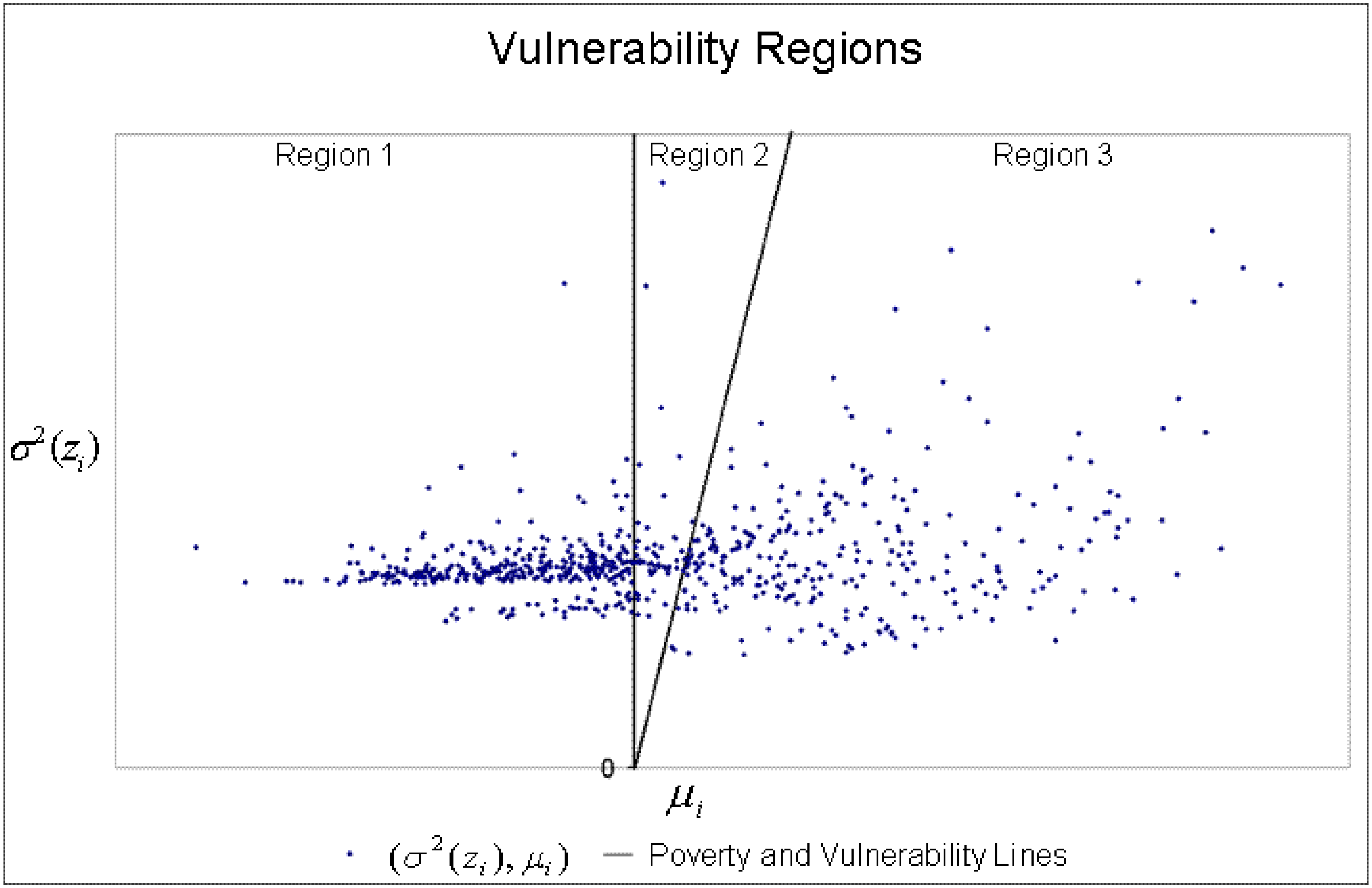
$$G(c^i) \equiv (\prod_{t=1}^{T} c_t^i)^{\frac{1}{T}}$$

$$\begin{aligned} V^i &\equiv U(z) - \mathrm{E}U(c^i) \\ P^i &\equiv U(z) - U(G(c^i)) \\ R^i &\equiv U(G(c^i)) - \mathrm{E}U(c^i). \end{aligned}$$

$$\begin{aligned} V^i &= e^{2\sigma^2(z^i)-\mu^i} - 1 \\ P^i &= e^{-\mu^i} - 1 \\ R^i &= e^{-\mu^i}[e^{2\sigma^2(z^i)} - 1]. \end{aligned}$$

A person is vulnerable whenever $2\sigma^2(z^i) - \mu^i > 0$, or consumption is not sufficient to offset variability.

Figure



Vulnerability Regions
Region 1
Region 2
Region 3
$\sigma^2(z_i)$
0
μ_i
$(\sigma^2(z_i), \mu_i)$
Poverty and Vulnerability Lines

New Determinants of Vulnerability

	Vulnerability =	Poverty +	Risk
	0.265** =	0.0640** +	0.201**
	(1)	(2)	(3)
HH Size in 93	0.0763**	0.0715**	0.00482
	(0.006)	(0.005)	(0.003)
Assets in 93	-3.14e-06	-3.20e-06*	5.77e-08
	(1.61e-06)	(1.49e-06)	(6.77e-07)
Unearned Inc in 93	-0.000161**	-0.000123**	-3.81e-05**
	(4.13e-05)	(3.48e-05)	(1.48e-05)
Educ Labor in 93	-0.121**	-0.122**	0.000297
	(0.014)	(0.009)	(0.009)
Indian	-0.506**	-0.458**	-0.0478
	(0.084)	(0.028)	(0.077)
Pop Density > 500	-0.243**	-0.226**	-0.0169
	(0.047)	(0.031)	(0.032)

Conclusions

Hard to know the accurate theoretical model to predict consumption and estimating multiple dynamic models is quite demanding.

We take a different route for estimating more forward-looking measures of chronic vulnerability using econometric methods.

Estimate the distribution of unexplained risk and use FGLS - results not very different from traditional measures.

Predict future consumption outcomes using the variance of unexplained risk - gain new insights on vulnerability.

When predicting the future, risk becomes larger but that risk is less predictable.