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Quantifying Vulnerability to Poverty: A Proposed Measure, with Application to Indonesia

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Abstract: Vulnerability is an important aspect of households' experience of poverty. Many households, while not currently "in poverty" recognize that they are vulnerable to events that could easily push them into poverty - a bad harvest, a lost job, an unexpected expense, an illness, an economic downturn. Most operational measures define poverty as some function of the shortfall of current income or consumption expenditures from a poverty line, and hence measure only poverty at a single point in time. We propose a simple expansion of these measures to quantify "vulnerability" to poverty. We define vulnerability as a probability, the risk a household will experience at least one episode of poverty in the near future. A household is defined to be vulnerable if it has 50-50 odds or worse of falling into poverty. Using these definitions we calculate the "Vulnerability to Poverty Line" (VPL) as the level of expenditures below which a household is vulnerable to poverty. This VPL allows the calculation of "Headcount Vulnerable Rate," the proportion of households vulnerable to poverty, which is the direct analogue of the "Headcount Poverty Rate."

We implement this approach using two panel data sets from Indonesia. We first show that if poverty line is set so that the headcount poverty rate is 20 percent, the proportion of households that are *vulnerable* to poverty is around 30 to 50 percent. So in addition to the 20 percent that are currently poor (hence are by definitions vulnerable to poverty), an additional 10 to 30 percent of the population is at substantial risk of poverty. Second, we illustrate the usefulness of this approach by examining differences in vulnerability between households by gender, level of education, urban-rural areas, land holding status, and sector of occupation of the household head. The conclusion speculates on the policy implications of these high levels of vulnerability.

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I) Introduction

One aspect of poverty that emerges strongly from people's descriptions of their experience is the notion of vulnerability (Beard, 1998). Many households, while not currently in poverty, recognize that they are vulnerable and that events could easily push them into poverty — a bad harvest, a lost job, an unexpected expense, an illness, a lull in business.[1] This aspect of vulnerability is not captured when poverty is defined as a function of the shortfall of *current* consumption expenditures from a "poverty line" (current consumption expenditures deficit or CCED concept).[2]

We propose a simple expansion of these static poverty measures to include vulnerability. Vulnerability is defined as the risk a household will fall into poverty in the future, and we propose a simple empirical measure that allows the setting of a "Vulnerability to Poverty Line" and thereby estimates of the "Headcount Vulnerable to Poverty Rate," which is commensurate with traditional headcount poverty rate. While the proposed quantitative measure does not begin to capture all of the complex, multifaceted, dimensions of the concept of vulnerability, this measure at least begins to put vulnerability on a par with static poverty measures in analytic and policy interest.

[1] In the developed countries context, Goodin *et al* (1999) find that much income instability is strongly associated with ordinary lifecourse events. In addition to traditional lifecourse events driven by age, people now have increasingly to cope with new ones, in particular separation, divorce, and early retirement.
[2] Examples of CCED measures of poverty are the FGT poverty indices from Foster, Greer, and Thorbecke (1984) as elaborated in Ravallion (1994) and many World Bank Poverty Assessments.

II) Defining Vulnerability

Definitions. While *vulnerability* is a complex concept, to begin quantification we must both simplify and use what is measured. We define our empirical measure of vulnerability as the risk a household will fall into poverty at least once in the next few years. This means that a household's vulnerability is measured as a probability, hence households have greater or lesser degrees of vulnerability. Since the future is uncertain, the magnitude of vulnerability rises with the time horizon, so vulnerability over the next week will be quite low, over a year higher, and over several years the risk will be higher still. The *vulnerability* of household *h* for *n* periods (denoted as R(·) for "risk") is the probability of observing at least one episode of poverty (in the usual CCED notion that real current consumption expenditures, *e*, are less than the poverty line) for *n* periods, which is one minus the probability of no episodes of poverty:

$$(1) \qquad R(n, PL) = 1 - \left[(1 - P(e_{t+1}^{h} < PL)) * \ldots * (1 - P(e_{t+n}^{h} < PL))\right]$$

Four points on this concept. First, since expenditures at time *t* are known, it is also known whether a household is currently in poverty or not. In the future, however, many households currently in poverty will rise out of poverty in the next n periods, so the future vulnerability of the currently poor is less than one. Second, the poverty line (PL) is time invariant because the household's total real expenditure *e* is appropriately deflated, so that a constant poverty line on those expenditure units represents constant levels of welfare over time. Third, by defining the notion in terms of observed expenditures, this measure of vulnerability already incorporates the existence and use of coping mechanisms. Some households may face large income variability and risk but have adequate mechanism to smooth over income changes and maintain expenditures relatively constant (e.g. savings, borrowing, informal or formal insurance). Hence observed expenditure vulnerability reflects both income risk and the utilization of smoothing.

Fourth, as a technical point, this is not the probability of at least one episode in n periods, but is a counterfactual: if one faced the one period ahead risk for n periods, what is the probability of one of those periods having an episode of poverty. The more realistic problem of the evolution of poverty over time, where we take seriously the time scale of the observation of expenditures (which is usually one month) and calculate the evolution of expenditures following some dynamic process and calculate the probability of at least one month, say in 36 months, being in poverty, is sufficiently more complicated, so we are not doing it that way.

While each household has some "vulnerability" (even millionaires could end up destitute), we want a more concrete measure of the number of households which are "vulnerable." We define a household as *vulnerable* if the risk in *n* periods is greater than a threshold probability level *p*:

$$V_t^h(p,n,PL) = I\left[R_t^h(n,PL) > p\right] \quad (2)$$

where I[·] is an indicator function. So, while vulnerability is a risk and comes in degrees (between zero and one), being *vulnerable* is a state (either zero or one).

We take the threshold probability level that defines a vulnerable household to be 0.5. This has two attractive features. First, 50-50 odds is a nice "focal" point and it makes intuitive sense to say a household is "vulnerable" if it faces even odds or worse. Second, if a household is just at the poverty line and faces a mean zero shock, then this household has a one period ahead vulnerability of 0.5. This implies that, in the limit, as the time horizon *n* goes to zero, then being "in current poverty" and being "currently vulnerable" coincide.

Implementation. Take the first period in the expression for vulnerability. Define the change in expenditures in the natural way as $\Delta e_{t+1} = e_{t+1} - e_t$. Suppose that there is a time invariant trend (the expected increase in household h's income in each period, μ) and variability of the inter-temporal *change* in expenditures for each household (σ) — note this is not the usual variability *across* households. Then the probability of a household with expenditures in the current period of e_t falling into poverty in next period is just the probability that the negative shock to expenditures is greater than the current amount by which the household's expenditures exceed the poverty line (e_t –PL) plus the expected change in income (μ):

(3a) $$P(e_{t+1}^h < PL) = P(\Delta e_{t+1}^h < -(e_t^h - PL))$$ or

(3b) $$P(e_{t+1}^h < PL) = P((\Delta e_{t+1}^h - \mu^h)/\sigma^h < \{-(e_t^h - PL) - \mu^h\}/\sigma^h)$$

The latter probability is:

(4) $$P = \int_{-\infty}^{(PL-e_t^h-\mu^h)/\sigma^h} f((\Delta e_{t+1}^h - \mu^h)/\sigma^h)\, d\Delta e$$

where f(·) is the density function of Δe.

As usual, to make more progress we need to make more, and stronger, assumptions.

First, assume that household expenditures is expected to be the same in each period so that $\mu = 0$ and $E(e_{t+n}) = e_{t.}$ This assumption has two justifications. First, this is a plausible "base case" as a hypothetical question: *if* incomes were to remain constant but the household faced the variability of income it currently faces, what is the probability it will fall into poverty? Hence, one should think of the calculations below as answering the question: if the level of income did not change but each household had variability in their expenditures repeated for *n* periods, what fraction of households would end up having at least one observed episode of poverty? Second, this assumption is easily modified later if one is willing to make clear and explicit predictions about the expected future growth (or fall) in earnings (either on average or for specific households).

We also make the even stronger assumption that Δe_t is independently identically distributed (iid) in each period and that the distribution of the *changes* in expenditures (not necessary the level) is normal. The assumptions of inter-temporal independence and normality are made for convenience in calculation and either could be relaxed with a calculation that is more complicated.

With these two assumptions we can compute the level of "vulnerability" of a household for any given level of current expenditures (*e*) as:

(5) $$R(n, PL, e, \sigma) = 1 - \left(1 - \int_{-\infty}^{(PL-e)/\sigma} N(0,1) \right)^n$$

We can also measure the number of households that are "vulnerable" by creating a "Vulnerability to Poverty Line" (VPL) as a function of the period length, probability of poverty, and the variability of the household's expenditures. The VPL is that level of expenditures such that, beginning from that level in period t, the probability of at least one episode of poverty in n periods is just *p*:

(6) $$VPL(p, n, PL, \sigma) \ solves \ 1 - \int_{-\infty}^{(PL-VPL)/\sigma} N(0,1) = [1-p]^{1/n}$$

A quick illustration of what these numbers would be. Suppose that mean (log) per capita expenditures is 200 and the poverty line is half of that, 100, and p = ½ is the vulnerability threshold. Table 1 provides values of the VPL for a combination of years into the future and variability of the change in household expenditures. The variability is expressed as the standard deviation of the inter-temporal change in expenditures over the mean level of 200.

Table 1: Calculation of hypothetical *Vulnerability to Poverty Lines* as a function of expenditure variability and period (n). Values of VPL(0.5,n,100,σ).

Years:	Ratio of standard deviation of household changes in expenditures to mean expenditures		
	0.5	0.25	0.10
2	152.5	127.5	111.25
3	**182.5**	**142.5**	**116.25**
4	197.5	147.5	118.75
5	212.5	157.5	123.75

The VPL behaves as expected: it is higher the larger the variability in expenditures. If the vulnerability horizon is three years ahead and if the variability of inter-temporal changes in expenditures is ½ of mean expenditures (100), then the VPL(0.5,3,100,100) is 82.5 percent higher than the poverty line, whereas if the variability of household expenditures is only 10 percent of mean income the VPL(0.5,3,100,20) is only 16.25 percent higher than the poverty line.

Increasing the horizon increases the VPL, and by a greater amount the higher the variability. So, if variability is high (50 percent of mean income), moving from a 3 year horizon to a 5 year horizon increases the VPL from 182.5 to 212.5 (higher than mean expenditures), an increase of 30 units. In contrast, if variability is low (10 percent of mean expenditures), then the same increase in horizon only increases the VPL by 7.5 units (from 116.25 to 123.75).

III) Estimates from Indonesian Data

This section has three sub-sections. First, estimating the variability in income with some accounting for measurement error. Second, computing the average vulnerability and number of households that are either "in poverty" and "vulnerable to poverty." Third, calculating vulnerability and proportion vulnerable by various household characteristics.

A) *Variability in Expenditures and Measurement Error*

Obviously in all of this, the key missing item is the variability of expenditures experienced by households over time. In a single cross section one can only estimate the variability of expenditures *across* households. With a panel with only two observations per household one could have an estimate of the variability of expenditures household by household, but only with extremely large imprecision. However, one can use such a panel to estimate the variability of expenditures by groups of households.[3] For instance, landless households versus land owning households, or households with differing levels of education could face different variability of their incomes.

We are almost uniquely blessed in having not one, but *two* independent panel data sets to estimate this variability. We use the two different panel data sets, the "Mini-Susenas" and "100 Village Survey," to estimate standard deviations of the change in expenditures for various types of households. The Mini-Susenas, with 10,000 HH sample, is a smaller version of the regular Consumption Module Susenas (the National Socio-Economic Survey), which has 65,000 HH sample. The Mini-Susenas survey was

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[3] An obvious extension is to estimate the variability as a function of a number of HH characteristics with a multivariate procedure and then use the HH's predicted variability in the vulnerability analysis.

first conducted in December 1998 and then repeated in August 1999 on the same sample frame, however only around 80 percent HH sample were surveyed in both rounds, providing a panel of 7,585 HH.[4] The 100 Village Survey was a panel survey that was first carried out in May 1997 for 12,000 HH in 100 villages (which include some urbanized areas, but no major cities) and repeated in August 1998, re-sampling only 2/3 of the households, providing a panel of 8,140 HH.[5] Both surveys were conducted by Statistics Indonesia (BPS), with the first round of Mini-Susenas was funded by UNDP while the 100 Village Survey was funded by UNICEF.[6]

The panels of households in both data sets make it possible to estimate the variability of changes in expenditures for households in category J:

$$(7) \qquad \sigma_{\Delta e}^{J} = \sqrt{\frac{\left(\Delta e_h^J - \Delta \overset{-J}{e_h}\right)^2}{N_J - 1}}$$

Notice this is the household specific variance, and hence a macroeconomic shock that left all households incomes changed by exactly the same amount would not reveal any household specific risk. This is a limitation of the procedure for estimating household variability from panels with only two observations.

However, there is an even more serious problem with this procedure, namely measurement error. In most CCED poverty analysis, households are classified by the *measured* expenditures. However, measured expenditures are only a very, very, rough

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[4] For more details on Mini-Susenas, see BPS (2000).
[5] See Suryahadi and Sumarto (1999) for more description of the 100 Village Survey.
[6] While the total sample size of Mini-Susenas is smaller than 100 Village Survey, the former is nationally representative while the latter is not.

measure of actual expenditures. Observed household expenditures at time t can be decomposed into the "permanent" (*P*) component of expenditures (the part which is time-varying but is expected at time t to persist), a "transitory" (*T*) component of expenditures (time varying and expected not to persist), and a measurement error term (*v*):

(8) $$e_h^t = e_h^{P,t} + e_h^{T,t} + v_h^t$$

If the three variances (σ^2) are uncorrelated, then ratio of measurement error (or "noise") to total variance is:

(9) $$\sigma_v^2 / (\sigma_P^2 + \sigma_T^2 + \sigma_v^2)$$

How large is this noise to signal ratio in measured expenditures? A wide variety of evidence suggests that in cross sectional surveys measurement error is somewhere between 1/3 to ½ of the total variance (see appendix for evidence with these data sets).[7]

Measurement error is typically ignored in poverty analysis for two reasons. First, since measurement error will tend to attenuate differences, and hence "flatten" poverty profiles by lowering the gap between groups, the direction of the bias is known (unless of course there are differences in measurement error across groups). Second, and more importantly, it is not clear what can be done about it.

[7] The method used to estimate measurement error in the appendix is similar to that used by Luttmer (2000).

However, there are two good reasons why measurement error cannot be ignored in vulnerability analysis. First, in estimating vulnerability, if the standard deviation of "true" expenditures is less than the observed variability due to measurement error, this will imply that the level of vulnerability faced by households will be overstated. The analysis of vulnerability using the estimates uncorrected for measurement error can be thought of as measuring the likelihood a household will have an episode of *appearing* to be in poverty, which could either be that they are actually in poverty or that there is measurement error in their expenditures.

Second, taking of first differences exacerbates measurement error by reducing the role of permanent expenditures in the total expenditure variability. Assuming that the variances of permanent, temporary, and measurement error are constant across time, then the ratio of noise to noise plus signal in the changes in expenditures is:

$$(2\sigma_v^2 - 2\sigma_{v_{t,t-1}}^2)/((2\sigma_P^2 - 2\sigma_{p_{t,t-1}}^2) + (2\sigma_T^2 - 2\sigma_{T_{t,t-1}}^2) + (2\sigma_v^2 - 2\sigma_{v_{t,t-1}}^2))$$

In the special case in which permanent income is time invariant and the innovations in temporary and measurement are uncorrelated with the previous period's innovation, then this implies that the measurement error problem in estimating changes is worse by eliminating the permanent component by first differencing:

$$\text{(10)} \qquad \frac{\sigma_v^2}{\sigma_T^2 + \sigma_v^2} > \frac{\sigma_v^2}{\sigma_P^2 + \sigma_T^2 + \sigma_v^2}$$

So, while we can estimate the latter expression from a cross section, to move to the former requires some estimate of the permanent versus transitory innovations and the persistence of "permanent" innovations to expenditures.

As a provisional measure, we shall do two vulnerability calculations in the following sub-sections. First, using the estimate of the standard deviations of changes in expenditures, in aggregate and for groups of households. Second, using the estimate of the standard deviation of incomes scaled back by the estimated measurement error from table A1 in the appendix.

B) Estimating the Level of Vulnerability

In this sub-section we estimate VPLs and headcount measures of vulnerability in both the Mini-Susenas and 100 Village Survey data. Since the level of poverty at any point in time is (more or less) arbitrary, we simply choose the poverty line so that the headcount poverty rate in both data sets is 20 percent.[8] Using this poverty line and the measured standard deviation of expenditure changes, we can calculate the vulnerability for the total sample. If we take a 3 year horizon as the *n* and a vulnerability threshold of 0.5 for calculating the households who are vulnerable, the VPL and the proportion of households who are vulnerable are as presented in table 2.[9]

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[8] This rate of headcount poverty is not completely unreasonable. For discussions on the poverty rates in Indonesia around the time of data collections, see Suryahadi *et al* (2000).
[9] All empirical vulnerability calculations using both Mini-Susenas and 100 Village Survey data sets, with the results presented in tables 2 and 5, are based on May 1997 prices.

Table 2: Estimates of Vulnerability and Proportions of Vulnerable HH's When Headcount Poverty is 20 Percent of the Population (May 1997 Prices)				
	Mini Susenas (December 1998 - August 1999)		100 Village Survey (May 1997 - August 1998)	
	Ignoring measurement error	Net of measurement error (30%)	Ignoring measurement error	Net of measurement error (50%)
Mean of log percapita expenditures in the initial period	10.901	10.901	10.730	10.730
Inverse of mean of log percapita expenditures (Rp/month)	54,251	54,251	45,687	45,687
Standard deviation of changes in log expenditures during the period	0.412	0.288	0.462	0.231
Yearly standard deviation of changes in log expenditures	0.617	0.432	0.370	0.185
Yearly coefficient of variability	0.057	0.040	0.035	0.017
Yearly probability of falling to below poverty line	0.238	0.154	0.137	0.015
Average vulnerability for three annual shocks	0.577	0.395	0.358	0.043
Average vulnerability three years ahead	0.406	0.367	0.358	0.233
Vulnerability poverty line [VPL(0.5,3,PL)]	10.967	10.815	10.629	10.477
Headcount vulnerable rate	58.91%	47.49%	42.10%	30.18%
Ratio of vulnerable to poor	2.95	2.37	2.11	1.51

The results with the usual standard deviations, which would ignore measurement error, show very high levels of vulnerability, 59 percent in Mini-Susenas and 42 percent in 100 Village Survey. In Mini-Susenas, the estimated yearly standard deviation of changes in log expenditures is 0.617, while the mean of log expenditures is 10.90, resulting in a ratio of 0.0566.[10] This implies that for a typical person in this sample, if the headcount poverty rate is 20 percent, the probability of at least one episode of apparent poverty in three years is 58 percent, while the probability that this person will be in poverty at least once in three years is 41 percent. To be "invulnerable" to poverty when

[10] This is a handy ratio, but it is not the "coefficient of variation" as this is the ratio of the standard deviation of *first differences* to the average of the *level*. We call this ratio the "coefficient of variability."

facing such large variability in expenditures requires a level of log expenditures of at least 10.967 (which is called "Vulnerability to Poverty Line"), which is even higher than the mean (log) expenditures of 10.90. Because of this, 59 percent of the population is vulnerable to an apparent episode of poverty, almost three times of the currently poor.[11] The level of vulnerability in 100 Village Survey sample is lower because the coefficient of variability is smaller. With a coefficient of variability 0.0345, the proportion of vulnerable population is 42 percent, about twice the poor.

This is interesting that the Mini-Susenas shows a *higher* level of variability in expenditures, as this panel did *not* span the worst period of the crisis. One would have thought that the 100 villages data, by being conducted before and after the worst of the crisis would have much larger variability. There are a couple of possible explanations. First, we have done nothing about seasonality—because we can't. So perhaps the May to August comparison has less seasonal fluctuation than December to August. Second, the Mini-Susenas is nationally representative and perhaps the 100 villages population is, by virtue of being smaller, poorer, villages also less variable. Third, maybe the Mini-Susenas has worse inter-temporal measurement error — but we know of no way of checking that.

These estimates of vulnerability are probably too high as they do not account for measurement error. We try to address this by the admittedly crude expedient of reducing the estimated standard deviation of changes in log expenditure by the estimated measurement error from the appendix, i.e. 30 percent for Mini-Susenas and 50 percent

[11] One way of thinking about this vulnerability to poverty is a formalization of the concept of "near poor," which is often used to illustrate the sensitivity of poverty rates to the poverty line. Vulnerability defines "near poor" using a normalization based on the variability of changes in expenditures. This eliminates the arbitrary nature of defining near poverty line as simply a chosen percent above the poverty line.

for 100 Village Survey data. In this case the level of vulnerability of the household at mean income and with mean variability of Mini-Susenas is 0.4, implying a 40 percent chance of an episode of poverty in three years. It is still the case that even though the poverty line is chosen so that only 20 percent are "poor," nearly a half of the population (47 percent) are vulnerable to poverty, in the sense of facing even odds (or worse) of one episode of poverty in three years. The lower variability in 100 Village Survey, meanwhile, resulting in 30 percent headcount vulnerable rate.

These high levels of vulnerability confirm the voluminous literature based on qualitative assessments of the importance of vulnerability in the analysis of poverty. The poor at any point in time are only a fraction of those who must worry about, and struggle to avoid, falling into poverty.

These findings are also consistent with analysis of other definitions of vulnerability. Using a six-year panel on households in rural China, Jalan and Ravallion (1998) estimate the inter-temporal "coefficient of variability" for consumption expenditures of 53.2 percent. They also found that the inter-temporal "coefficient of variability" for consumption tends to remain roughly constant as mean consumption expenditures increase.

These results are also consistent with calculations and analysis of other definitions of vulnerability. Jalan and Ravallion (1999), using a six year panel on households in rural China, examine "chronic" and "transient" poverty by examining which households were either persistently poor (expenditures in each period below the poverty line), chronically poor (*mean* expenditures over all periods less than the poverty line but not poor in each period), transiently poor (*mean* expenditures over all periods above the poverty line but experiencing at least one episode of poverty), and never poor. The results, reproduced here in table 3, are consistent with a large level of "vulnerability," as even though only

6.2 percent of households were "always poor" and a cross section in any given year would find less than 20 percent poverty, 54 percent of the sample experienced at least one episode of poverty.

Table 3: Characterization of transient and chronic poverty in households from China over six years, 1985-1990.

	Chronically poor (mean expenditures below poverty line)		Transiently poor only (mean expenditures above poverty line)	Never poor
	Always poor	Not persistently poor		
Full Sample	6.21	14.38	33.38	46.03
Guangdong	0.40	1.04	18.31	80.25
Guangxi	7.12	16.07	37.38	39.43
Guizhou	11.90	21.20	40.17	26.73
Yunnan	4.88	18.04	35.55	41.53

Notes: Adapted from Jalan and Ravallion (1999), table 2.

Other panel evidence shows similar transitions in and out of poverty. A summary of research using panel data that matches poverty data in households with at least two observations in Baulch and Hoddinott (1999), reproduced here in table 4, shows that the fraction of households which have experienced an episode of poverty is at times much larger than either those who never experienced such an episode or those who were persistently poor. This is consistent with our findings that levels of vulnerability to poverty are much higher than poverty rates themselves.

Table 4: Changes in poverty from panel surveys in selected countries				
Country	Period	Headcount (%)		
		Always Poor	Sometimes Poor	Never Poor
Zimbabwe	1992/93-1995/96	10.6	59.6	29.8
Pakistan	1986-1991	3.0	55.3	41.7
South Africa	1993-1998	22.7	31.5	45.8
Russia	1992-1993	12.6	30.2	57.2
Ethiopia	1994-1997	24.8	30.1	45.1
Cote D' Ivoire	1987-1988	25	22	53
Notes: Adapted from Baulch and Hoddinott (1999).				

Of course the reverse side of vulnerability of the non-poor is that the poor are also escaping poverty. A relatively small number of households remain in poverty consistently. This suggests that "the poor" from time to time are not a fixed but fluid group of households.

C) Differences in Vulnerability

In addition to the *level* of vulnerability, there is also interest in capturing the fact that different groups face different levels of risk. For example, even though two groups may have the same level of expenditures and hence one group has the same headcount poverty measure as the other, it is possible that one of the groups faces a higher level of risk so that they are more vulnerable. In this section we use only the estimates with the measurement error corrected estimated standard deviation to compare levels of vulnerability across various groups of households as presented in table 5. A handy way to compare results across groups is to compare the ratio of those "vulnerable" to those "poor" as this indicates how relatively important transient poverty is for these groups.

Table 5: Estimates of poverty and vulnerability across groups

	Mean of log per capita expenditures in the initial period	Headcount poverty rate (%)	Yearly coefficient of variability	Average vulnerability for three annual shocks	Headcount vulnerable rate (%)	Ratio of vulnerable to poor
Using Mini-Susenas:						
By gender:						
a. Male	10.9009	20.50	0.0392	0.3899	47.11	2.30
b. Female	10.9071	21.23	0.0440	0.4410	50.97	2.40
By education:						
a. Less than primary	10.6840	32.04	0.0404	0.6611	64.94	2.03
b. Primary	10.8279	21.15	0.0381	0.4624	49.67	2.35
c. Lower secondary	11.0430	10.06	0.0399	0.2544	34.20	3.40
d. Upper secondary & higher	11.3333	4.24	0.0399	0.0783	17.69	4.17
By urban-rural:						
a. Urban	11.1640	7.93	0.0405	0.1697	29.10	3.67
b. Rural	10.7284	28.88	0.0389	0.5963	59.17	2.05
By land owning (rural households only):						
a. Landless	10.4631	58.30	0.0318	0.8732	75.74	1.30
b. Landed	10.7325	28.42	0.0390	0.5919	58.87	2.07
By sector:						
a. Agriculture	10.6567	33.76	0.0389	0.6837	65.79	1.95
b. Industry	10.9881	15.24	0.0381	0.2812	39.77	2.61
c. Trade	11.0661	10.55	0.0416	0.2575	36.33	3.44
d. Services	11.1270	9.46	0.0399	0.1867	30.50	3.22
Using 100 Village Survey:						
By gender:						
a. Male	10.7197	20.47	0.0172	0.0481	30.80	1.50
b. Female	10.8450	14.53	0.0177	0.0100	22.66	1.56
By education:						
a. Less than primary	10.6357	24.78	0.0168	0.1184	35.56	1.44
b. Primary	10.7372	18.29	0.0178	0.0463	28.83	1.58
c. Lower secondary	10.8591	13.71	0.0171	0.0061	21.13	1.54
d. Upper secondary & higher	11.0797	6.74	0.0173	0.0001	12.69	1.88
By urban-rural:						
a. Urban	11.0174	5.52	0.0167	0.0002	10.29	1.86
b. Rural	10.6673	23.13	0.0174	0.0942	34.47	1.49
By land owning (rural households only):						
a. Landless	10.8799	9.84	0.0184	0.0083	18.92	1.92
b. Landed	10.6214	26.00	0.0171	0.1477	37.69	1.45
By sector:						
a. Agriculture	10.6038	26.87	0.0173	0.1818	39.00	1.45
b. Industry	10.8505	11.58	0.0165	0.0050	20.07	1.73
c. Trade	10.9185	7.71	0.0177	0.0033	14.21	1.84
d. Services	11.0045	6.96	0.0168	0.0004	12.70	1.82

Gender of household head. One of the most persistent gaps between the quantitative and qualitative measures of poverty is that the quantitative measures very rarely find that female headed households are less well off (or have higher poverty rates), while in qualitative and participatory poverty assessments female headed households are often identified as the poorest of the poor. There are three possible reasons for this discrepancy. First, inadequate accounting for economies of scale in household consumption expenditures in the quantitative estimates versus people's experience and perceptions (Dreze and Srinivasan, 1997). Second, the category of female headed households is heterogeneous as it includes households "headed" by females at the time of the survey because the husband was absent, but was providing remittances and households in which women are truly supporting themselves (and others) alone such as widows and divorced and single mothers. Third, is that while female headed households have the same level of expenditures, they are more vulnerable to shocks and hence more at risk of poverty.

Our calculations on the Mini-Susenas sample indicate that female-headed households have slightly higher mean per capita expenditures, but their poverty rate is slightly higher than male headed households.[12] Furthermore, the data suggest that female headed households have greater expenditure changes variability and, hence, higher proportion of vulnerable households (2.4 for female headed households versus 2.3 for male headed households). The 100 Village Survey sample also indicate that female-headed households have a slightly greater variability in expenditure changes than male headed households. However, in this sample their mean expenditures is much

[12] This indicates that female-headed households have higher expenditures variability *across households* than male headed households.

higher and their poverty rate is much lower and, hence, their headcount vulnerable rate is much lower than male headed households. In this data set as well, however, the ratio of vulnerable to poor households is slightly higher for female than male headed households (1.56 compared to 1.50).

This means that both data sets agree that female-headed households tend to have higher mean per capita expenditures and, at the same time, greater variability in expenditures changes than male headed households. However, the two data sets do not agree on the relative headcount poverty and vulnerable rates between the two groups of households, but agree on the ratio of both rates. Hence, these results give some light to, but stop short of resolving, the quantitative vs. qualitative puzzle for female headed households.

Educational level. The analysis of vulnerability by education level using both data sets in general gives expected results. The higher the level of education of household head, the higher mean of per capita expenditures and the lower the poverty rate. There is no particular pattern on the variability of expenditure changes with respect to the education level, but they seem to be roughly the same across the level of education. Therefore, the average vulnerability and headcount vulnerable rate are lower the higher the education level of household head. However, in relative terms, the ratio of vulnerable to poverty rate is increasing with education level. So, in the Mini Susenas data even though the poverty rate of the most educated is only 4.2 percent, 17.7 percent are vulnerable, while the result is less dramatic in the 100 villages data, it is still 12.7 percent vulnerable even in the highest education group.

Urban versus rural. In comparing urban versus rural areas in the 100 Village Survey sample, one must keep in mind that the "urban" areas in this survey do not include any major cities but rather are smaller cities and urbanized areas. Also, the data represent a period of a very severe crisis, in which many urban areas and occupations were hard hit.[13] Nevertheless, both data sets seem to agree on many aspects. Urban households have a much higher mean of per capita expenditures and much lower poverty rate than rural areas. The variability of expenditure changes in both areas seem to be roughly the same, but the two data sets disagree on the ordering. The resulting average vulnerability and headcount vulnerable rate are much lower in urban than rural areas. However, as with education, the ratio of vulnerable to poor households is much higher in urban than rural areas, partly because it begin from a lower base. But the urban results in the Mini-Susenas show what a difference vulnerability analysis can make – while poverty is only 8 percent and hence might be thought to be "not on issue," almost 30 percent of households are vulnerable.

Landed versus landless rural households. Interestingly, in this category the two data sets disagree on just about everything. According to the Mini-Susenas sample, rural households which own land have higher mean of per capita expenditures, lower poverty rate, higher variability in expenditure changes, lower average vulnerability, lower headcount vulnerable rate, and higher ratio of vulnerable to poor than the rural landless. On the other hand, the 100 Village Survey sample suggest that it is the rural households which do not own land which have such characteristics. At this juncture, it is still a puzzle as to why the two data sets convey completely conflicting stories. This disagreement is not a weakness of this study, but reveals a strong feature of this study, as we actually have and are using two independent data sets to corroborate results. Had we not used the second data set, we then would not have been able to report the difference (as in the first version of the paper).

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[13] See Poppele *et al* (1999) and Sumarto *et al* (1998).

Sector of occupation. Both data sets indicate that households in agriculture sector have the lowest mean per capita expenditures and the highest poverty rates. This is followed by manufacturing, trade, and services as the sector with the highest mean per capita expenditures and the lowest poverty rates. Meanwhile, variability of expenditure changes is roughly the same across sectors. Hence, the ordering of sectors by average vulnerability and headcount vulnerable rate is the same as poverty rate ordering. However, the ordering of ratio of vulnerable to poor is basically reversed. "Trade" has the highest ratio of vulnerable to poor, followed by services, industry, and then agriculture. Especially in the Mini-Susenas, where in the trade sector poverty is 10.6 percent but vulnerability is 36 percent, the importance of acknowledging variability is obvious.

IV) Conclusions and Implications

Like the notion of poverty itself, the concept of "vulnerability" to poverty is complex and multifaceted and will never be adequately summarized in a single measure. However, we think the definitions and measures proposed here provide a step forward in the dialogue on vulnerability to poverty as it allows application of household survey data to explore the notion of vulnerability quantitatively. The strong assumptions we make allow just one additional parameter, the standard deviation of inter-temporal changes in expenditures, to open up an entire line of analysis of vulnerability. This also means that one can estimate "coefficients of variability" by group with one data set and then apply these to subsequent cross sections to do vulnerability analysis, even without a panel.

We find that vulnerability is important quantitatively. In a sample in which the headcount poverty rate is set to be 20 percent of the population, an additional 10 to 30 percent of households are "vulnerable" to poverty (that is, at even odds of at least one episode of poverty in 3 years), and hence 30 to 50 percent of the population is "vulnerable" to poverty. We also find significant differences across groups that would have been missed by the static measures of current consumption expenditures deficit (CCED) poverty.

Expanding the analysis of poverty to vulnerability has several policy implications. First, the issue of targeting becomes more problematic. Are programs intending to reach only the "persistently poor"? If so, they will fail to capture a large swath of the population who, while they may not be "always poor," experience episodes of poverty. Without the ability to observe *current* incomes or expenditures on a frequent basis, targeting to the presently poor would be very difficult. That is, suppose a beneficiary group was chosen based on observed incomes at one point in time, how accurate would that be if the same beneficiary group were maintained for one year? Two years? Three years? Obviously the targeting accuracy deteriorates the larger the household variance and the longer the period.

Second, this raises the issue of risk and security. Many "social protection" or "social insurance" schemes (e.g. unemployment insurance, disability benefits, and health insurance) attempt to reduce the variability of income by providing transfers *not* to the poor but to those that have experienced shocks. In this sense these programs act more as a mountain climber's "safety rope" (a rope that fixed at a progressively higher levels and protects the climber from a fall of more than a fixed distance) than as a trapeze artists "safety net" that catches only at the bottom. That is, while often both are referred to as "safety nets," there is an analytic distinction between social *insurance* programs in which the benefits are contingent on the realization of some event — unemployment, flood, fire, health shock, old age, disability (safety ropes) — and *poverty* programs in which the benefits or participation are intended to be contingent on expenditure (or income) level (safety nets). It may well be that insurance programs will be as important as poverty programs in reducing vulnerability.[14]

Third, this may provide insights into the political economy of targeting. While there is only a small proportion of the population who are chronically poor (and one would conjecture these would tend to be relatively politically powerless), there are many many more who are vulnerable to poverty and would, for entirely self-interested reasons, be interested in programs that reduce the risks they face. In models in which the budget for poverty programs is endogenously determined by majority voting, programs that are well targeted to the poor can be *worse* for the poor than programs supported by the

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[14] For more discussions on this, see Sumarto *et al* (2000).

"middle" group interested in reducing their vulnerability (Gelbach and Pritchett, 1997 and 1999). In their model, this is because the budget for well targeted programs is so low compared to programs with more broad based support that the poor are worse off with a larger share of a smaller pie.

Finally, vulnerability may alter the target groups for poverty or social insurance programs. In the Indonesian context, certain occupational groups (such as landless rural workers, urban informal sector workers (e.g. scavengers), or fishermen) or certain socioeconomic groups (e.g. widows) *may* have quite highly variable incomes and hence merit attention even if their average level of expenditures is not *on average* too much different from others. This is a possibility to be considered on a policy level, as it is not clear that this vulnerability can be properly identified or measured, or once identified there may be no programs that would be able to address this vulnerability.

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Appendix: Estimating Measurement Error

One easy heuristic way in estimating measurement error is to estimate any equation with expenditures as the right hand side variable using both OLS and instrumental variable techniques (such as Engel curve). Since the expression for the attenuation bias in OLS estimates in a bivariate regression is:

(11) $$\beta_{OLS} = \beta\left(1 - \frac{\sigma_v^2}{\sigma_*^2}\right)$$

Where "*" represents the total (noise plus signal). If there exists an instrumental variables estimate that is consistent, then one minus the ratio of the OLS to the IV estimate is an estimate of the noise to total variance ratio. In this case, table A1 suggests that roughly 30 to 50 percent of the measured variance across households is measurement error. This is very heuristic at this stage as this depends on classical measurement error, but since the right hand side is a non-linear (i.e. natural log) transformation of a variable (total expenditures) that is in the denomination of the left hand side, the classical measurement error is not correct and one would have to apply the more advanced technique for non-linear measurement error (a la Hausman, Newey, and Powell (1995)).

Table A1: Estimating measurement error using estimates of the Engel Curve (food share on ln(expenditures/person))				
	Mini-Susenas (December 1998)		100 Village Survey (May 1997)	
	OLS	IV	OLS	IV
Constant	2.434 (95.53)	3.297 (83.96)	1.552 (58.15)	2.321 (50.95)
Ln expenditures	-0.161 (-68.78)	-0.240 (-66.59)	-0.079 (-31.60)	-0.150 (-35.39)
R-squared	0.384	0.291	0.109	0.018
N	7,585	7,585	8,140	8,140
Ratio of OLS to IV estimate	0.670		0.523	
Estimate of noise to total variance ratio	30%		50%	

Notes:

B) t-statistics in parenthesis.

C) Instruments for expenditures are education, gender, housing conditions, and asset ownership variables.

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