# Poverty, Risk and Accumulation: Pro-Poor Policies when Dynamics Matter

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## Abstract

Poverty and vulnerability measures provide a basis for the targeting of policy interventions. In applied work typically static versions of these measures are used so that the effect of asset changes on welfare is ignored. Unless the policymaker's concern with household welfare is myopic, policy design requires welfare measures that incorporate the dynamics of asset accumulation.

We use a simple microeconomic growth model to show that the use of a static or dynamic welfare measure affects the choice between three types of interventions (transfers, productivity enhancements and reductions in risk). We also show (using data for rural households in Zimbabwe) that the composition of the group of low-welfare households may change dramatically over time. For both reasons static poverty (or vulnerability) measures may be a poor basis for policy.

Using the Zimbabwe example we show that when it is not feasible to estimate a structural dynamic model then the accuracy of existing regression-based vulnerability measures can be greatly improved by including asset measures in the regression.

# 1 Introduction

It has long been recognised that a substantial part of poverty in developing countries is transient rather than chronic. A recent survey of panel data studies of “poverty dynamics” - movements in and out of poverty - concluded that in “most of the studies, the category of ‘sometimes poor’ is larger, sometimes by a considerable amount, than the ‘always poor’.” (Baulch and Hoddinott, 2000, p. 6). Clearly, in such circumstances welfare assessments based on consumption data from cross-section household surveys may be misleading: consumption can be atypically low (or high) as a result of a negative (or positive) shock. Obviously, targeting pro-poor policy interventions on particular categories of households (e.g. those without livestock) identified in a poverty assessment makes sense only if households are expected to remain in such categories for some time without the intervention.

That under risk a household’s current consumption may not be a good indicator of its welfare explains the recent emphasis in the poverty literature on vulnerability (*e.g.* World Bank, 2001). Given the distribution of consumption at some point in time vulnerability is usually defined either as a high level of expected poverty or as a low level of expected utility. In either case vulnerability has both a deterministic component (mean consumption or utility at the chosen date) and a stochastic one (volatility around that mean, reflecting the household’s exposure to risk and the limited scope for risk coping). Vulnerability measures can be decomposed accordingly into a deterministic ‘poverty’ component and a stochastic ‘risk’ component (Ligon and Schechter, 2003).

The literature implicitly assumes that in the absence of risk poverty (measured by current household consumption) is a good proxy for household welfare, both in a descriptive sense and as a criterion for policy targeting. In this paper we argue that this can be very misleading. Except in the improbable case of complete markets (including markets for assets, credit and insurance) consumption will change over time as households invest in assets (*e.g.* education, financial assets, or livestock). Clearly, current consumption can then be a poor indicator of household welfare, even in the absence of risk. Since development policy is concerned with impacts over a period of a generation or more it must, at least in principle, be based on a model which describes the evolution of household welfare over time. In practice, however, development practicioners have relied heavily on static poverty (or vulnerability) measures.

In this paper we consider the implications of the dynamics of asset accumulation for policy design. We define vulnerability in terms of expected discounted utility over an extended (possibly infinite) period. (This is equivalent to the traditional vulnerability measure for a 1-period horizon and to the poverty concept if, in addition, there is no risk.) A government concerned with long-run welfare would target interventions *not* on those who are currently vulnerable but on those who are structurally vulnerable, *i.e.* the households who will remain or become vulnerable. (An analogy is the economic analysis of unemployment where the focus has shifted from the total stock of unemployed to the stock of long term unemployed and the flows into and out of unemployment.)

The distinction between current and structural vulnerability is important. We show that under incomplete financial markets there is substantial scope for Pareto improving redistributions, even between agents with the same current vulnerability. For example, if two households are identical in terms of current vulnerability but one is vulnerable because of low productivity (e.g. poor soil quality) and the other one because it currently has few assets, then redistribution in favor of the second household can be Pareto improving since such redistribution can act as a substitute for a missing credit market.

Would the use of a dynamic welfare concept in policy design lead to different decisions? This could happen in two ways: it might lead to achoice of different policies and it could lead to targeting on different groups. We consider both possibilities in this paper.

We use a simple microeconomic growth model in which there is scope for three types of public interventions: transfers between households, measures to increase productivity (e.g. through education) and policies that reduce risk. We show that the choice between these instruments is quite sensitive to whether or not the welfare measure used is myopic (such as the poverty and vulnerability measures currently in use). In particular myopic measures are biased in favour of transfers. When the dynamics of assets accumulation are taken into account productivity-enhancing or risk-reducing policies become much more attractive.

The second possibility is that the use of static welfare measures leads to targeting of interventions on the wrong groups. This would happen if a household's welfare would substantially change over time, reflecting either investment (under credit constraints) or disinvestment (following a positive shock). Targeting on the basis of static measures would then potentially involve type I and II errors: some households that would not need support would receive it and vice versa.[1] We investigate whether this is empirically important using a stochastic growth model estimated using a panel dataset for rural households in Zimbabwe. We show that the composition of the group of low-welfare households changes rapidly over time so that (at least for this dataset) there is indeed a serious danger of mistargeting.

Hence using a dynamic welfare measure is not just conceptually attractive: it may greatly improve both targeting and the choice of suitable interventions. However, implementing such a measure is of course costly, requiring the specification and estimation of a stochastic growth model. We therefore use the Zimbabwe example to assess the accuracy of simpler, regression-based vulnerability measures. Regressions which relate consumption to time-invariant (or slowly changing) household characteristics and (*ex post*) shock measures but not to assets can be misleading in identifying vulnerable households. We find, however, that targeting can be greatly improved if lagged asset ownership (in our case: livestock) is included in the regression.

[1]Type I and II errors in targeting of course also occur in a static context (see e.g. Cornia and Stewart, 1996, for a discussion of "F-mistakes" - failure to reach some of the target group - and "E-mistakes" - excessiveness in the sense that some of the benefits accrue outside the target group). Our focus is on one particular reason for such errors: the use of myopic measures for targeting when the target group is defined in terms of future outcomes.

The structure of the paper is as follows. In the next section we briefly review the literature on the concept and measurement of vulnerability and we present our dynamic extension. In section 3 we analyse how vulnerability changes over time and we derive policy implications in terms of the types of households to be targeted for intervention. In particular we show that a focus on those currently vulnerable can be inappropriate. Pareto efficiency requires discrimination within this group, depending on how their welfare is expected to change over time. In section 4 we use an analytically tractable growth model to assess the effectiveness of three types of interventions, using both static and dynamic welfare measures. This shows that the choice of instrument is quite sensitive to the period considered. Hence whenever a government is concerned with long-run welfare the use of static welfare measures can lead to an inappropriate choice of policies. We also show in this section how the composition of the group of vulnrable households changes dramatically over time. In section 5 we use the Zimbabwe model as the data generating mechanism for regression-based vulnerability measures. We assess the accuracy of these measures for various specifications of the regression. We find that (for this dataset) quite acceptable results can be obtained if measures of lagged asset ownership are included in the regression. Section 6 concludes.

## 2 Vulnerability Measures

In applied work vulnerability is usually understood as the *expected* poverty of a household. Vulnerability is then calculated as a probability-weighted average of consumption in various states of nature (*e.g.* Christiaensen and Subbarao, 2001):

$$V = \int_0^z p(c,z)dF(c) \tag{1}$$

where $z$ is a poverty line, $c$ consumption, $F(c)$ the distribution of consumption at the date considered and $p(c,z)$ a poverty measure, *e.g.* a member of the Foster-Greer-Thorbecke class

$$p(c,z) = \left[\frac{\max(z-c,0)}{z}\right]^\alpha$$

where $\alpha$ is a non-negative parameter. The distribution $F$ is taken as given and reflects both the household's exposure to shocks and its response to risk, e.g. the use of assets for consumption smoothing.[2] Note that for the special case of the headcount measure ($\alpha = 0$) the vulnerability measure reduces to the probability that the household will experience poverty (in the sense that

[2] In applied work $F$ is often estimated from cross-section data. If panel data are available then $F$ can be estimated as the distribution of consumption *across time*, for a particular household. In this case the intertemporal mean $\bar{c} = (c_1 + \cdots + c_T)/T$ is considered as the permanent component of consumption and all deviations from this mean as transient. Jalan and Ravallion (2000) use this method for China and McCulloch and Baulch (2000) do so for Pakistan. This method allows for inter-household heterogeneity but imposes the restrictive assumption that $F$ is stationary.

$c < z$):

$$V = F(z). \tag{2}$$

This vulnerability measure is popular in applied work.[3]

The expected poverty concept in (2) seems a natural extension of the deterministic poverty concept. However, vulnerability thus defined can be inconsistent with the household's own assessment of its welfare. For example, an increase in risk (in the sense of a mean-preserving spread of $F$) reduces the welfare of a risk-averse household, but its vulnerability as defined in (2) may fall. For the Foster-Greer-Thorbecke class expected poverty will rise only for $\alpha > 1$ (Ligon and Schechter, 2003; cf. Ravallion, 1988). This rules out the two most popular members of the class: the poverty gap measure ($\alpha = 1$) would record no change when risk increases whereas the headcount ($\alpha = 0$) would (perversely) show an *improvement*, a reduction in vulnerability. Conversely, $\alpha > 1$ implies that the degree of absolute risk aversion increases with consumption (for $c < z$), contrary to much of the empirical evidence.

An alternative is to measure household welfare by expected utility and its vulnerability by the distance from some benchmark welfare level (e.g. Ligon and Schechter, 2003):

$$V = u(z) - Eu(c)$$

where $u$ is a weakly concave utility function and $z$ can be seen as a certainty equivalent poverty line. For $V > 0$ the household would be considered vulnerable.[4] The measure can be decomposed as

$$V = [u(z) - u(Ec)] + [u(Ec) - Eu(c)]$$

where Ligon and Schechter interpret the first term as the non-random part of vulnerability ('poverty') and the second term as the effect of risk.

Measuring vulnerability on the basis of equation (1) or on the basis of expected utility has some disadvantages. First, such methods are essentially static: they focus on a household's welfare at a particular moment. Secondly, the methods ignore any behavioral response to risk. Implicitly they assume that risk affects the volatility of consumption around the mean $Ec$ but not the mean itself. In fact risk affects the savings and investment decisions of households (except in very special cases) and thereby the mean consumption level. This effect can be very large but it can be measured

[3] The World Bank defines vulnerability as "the risk today to fall below the poverty line tomorrow" (Coudouel *et al.*, 2001, p. 37).

[4] Equivalently, vulnerability could be measured as $V = \max(u(z) - Eu(c), 0)$ in analogy with the headcount measure. Note that the cutoff at $z$ is applied to expected utility rather than to consumption $c$ in a particular state of nature. The alternative $V = u(z) - Eu(\min(c, z))$ (e.g. Calvo and Dercon, 2005) is problematic when amended so as to apply in a dynamic context. While in a static context the policy maker may consider outcomes above a certain level irrelevant for the assessment of vulnerability, this position is difficult to maintain in a dynamic setting where such outcomes may offset outcomes with $c < z$ (provided there is intertemporal substitutability or consumption can be stored in the body).

only if a structural dynamic model is used.[5] Finally, a household's vulnerability can be low either because it is not exposed to large shocks or because it is able to cope effectively with shocks. Policy makers would want to distinguish between the two cases. For example, a household may achieve consumption smoothing through means which are unnecessarily costly in terms of growth. There would then be a case for intervention (providing insurance to substitute for consumption smoothing through (dis)saving of liquid assets) but the case can be identified only if the household is classified as vulnerable in spite of its consumption smoothing. If this distinction is to be made then we must be able to estimate both actual and counterfactual vulnerability, the latter for the hypothetical case where the household faces no shocks. This requires, again, a structural model so that behavioral responses to risk are taken into account. With a proper structural model vulnerability can be assessed separately with and without risk so that the cost of the household's coping mechanism can be estimated.[6]

We extend the static utility-based concept, using discounted expected utility over a period of length (possibly infinite) $T$ as the household's welfare measure. From the perspective of $t = 0$ vulnerability $s$ periods ahead is defined by:

$$V_s(A_0, k_0) = E_0 \Sigma_{t=s}^{T+s} \beta^{t-s}[u(z) - u(c_t)] \tag{3}$$

where $A$ is a measure of the household's productivity, $k_0$ the initial capital stock, $\beta$ a discount factor, $c_t$ is the household's optimal consumption at time $t$, given $A_0$, $k_0$ and the distribution of future shocks. To implement this measure we need a model to describe the optimising behavior of the household, resulting in the optimal values $c_t$.

It is useful to distinguish between four types of determinants of household welfare and hence vulnerability. *First,* vulnerability is affected by determinants of total factor productivity such as the soil quality of the holding or the education of the household's members. *Secondly*, vulnerability reflects the household's asset ownership. *Thirdly*, vulnerability captures the household's exposure to shocks (*e.g.* unreliable rainfall) and, *finally*, its ability to cope with shocks (*e.g.* through insurance or the use of savings for consumption smoothing). Government interventions can reduce vulnerability through any of these four channels. Given a structural model the effect of such interventions can be evaluated.

[5] Thorbecke (2003, p. 13) notes that a fundamental feature of the approach we adopt in this paper is "that it incorporates the possibility of households deciding within an intertemporal framework to reduce their mean consumption to reduce consumption variability and risk".

[6] None of the existing measures is based on a structural model although some authors are well aware that vulnerability measures should be based on a dynamic analysis and that this "would require the structure of a proper dynamic model" (Ligon and Schechter, 2003, p. C101).

## 3 The Dynamics of Vulnerability

In this section we consider the question whether static welfare indicators (such as Foster-Greer-Thorbecke poverty measures or vulnerability measures in the expected poverty or expected utility class) can be used as a basis for policy. In this section we treat productivity $A$ as a constant.

Figure 1 illustrates the effect of household-specific productivity $A$ and initial assets $k_0$ on vulnerability. To focus on the impact of changes in assets we initially abstract from risk. The Figure is consistent with a wide class of micro growth models. All that we require is that (a) for any finite period a household's welfare is increasing in $A$ and $k_0$, (b) the capital stock converges to a steady state level $k^*$ which is independent of $k_0$, and (c) $k^*$ is increasing in $A$.

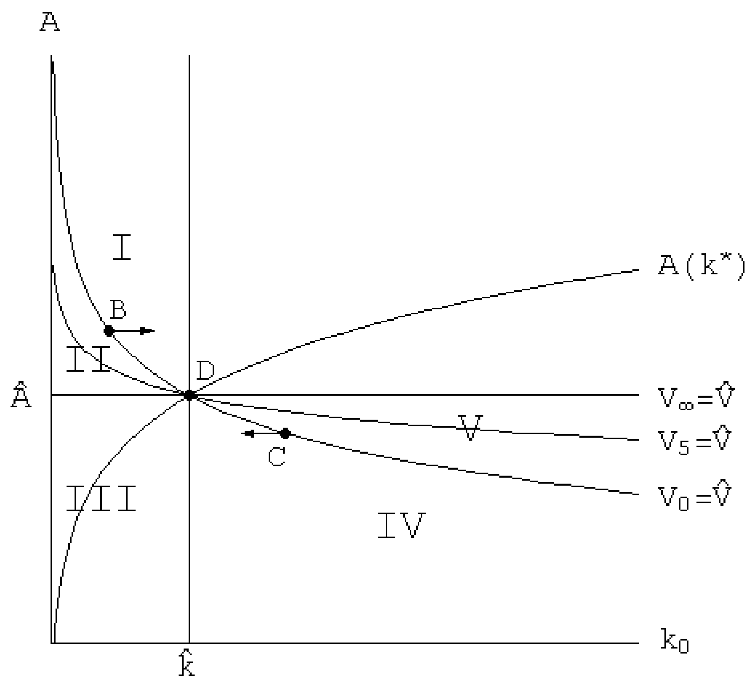


Figure 1: Productivity ($A$), initial capital ($k_0$) and vulnerability (for $s = 0, 5, \infty$)

The Figure shows three iso-vulnerability (IV) curves, defined by $V_s(A, k_0) = \widetilde{V}$ ($s = 0, 5, \infty$). For finite $s$ the IV curves are downward sloping: high productivity can compensate for low initial assets. As $s$ increases the locus rotates anti-clockwise. In the limit welfare is independent of initial conditions, as shown by the horizontal $V_\infty(A, k_0) = \widetilde{V}$ locus.

If $k_0 \neq k^*(A)$ then the household will adjust its capital stock. The steady state value $k^*$ is an increasing function of productivity; this relationship is shown as the locus $A(k^*)$. A household which starts at a point such as $B$ will accumulate capital (moving horizontally to the right) until it reaches the $A(k^*)$ locus. Conversely, a household starting at point $C$ will reduce its capital stock, moving to the left towards the $A(k^*)$ locus.

The IV curves and the $A(k^*)$ locus intersect in point $D$. It is intuitively appealing to use the coordinates of that point as the critical values for productivity and initial assets. This defines five areas in $(A, k_0)$ space, shown as $I, .., V$. Households with combinations of $A$ and $k_0$ values in areas $II, III$ and $IV$ are currently vulnerable: $V_0(A, k_0) > \widetilde{V}$. They have either low assets or low productivity or both. Note that if households were classified as vulnerable only on the basis of $k_0$ then those in areas $I, II$ and $III$ would be classified as vulnerable. Obviously, this taxonomy would introduce type I and type II errors: some households would be erroneously included in the vulnerable (those with high productivity, area $I$) while those with low productivity (but high $k_0$) would be erroneously excluded (area $IV$).

If $s$ increases (so that the policy maker is concerned about vulnerability at a more distant date) then area $II$ shrinks: given time to accumulate capital the households with the highest productivity in this area will escape from vulnerability (in the sense that beyond some critical value of $s$ $V_s(A, k_0) < \widetilde{V}$). Conversely, area $IV$ will expand: households in area $V$ with relatively low productivity will at some stage no longer be able to maintain $V$ below $\widetilde{V}$: $V_s(A, k_0) > \widetilde{V}$ for $s \geq s^*$ where $s^*$ is some critical value. In the limit area $II$ disappears and the vulnerable are those with low productivity (areas $III, IV$ and $V$).

The Figure shows that the group of currently vulnerable households (those in areas $II, III$ and $IV$) differs from the group of those who are structurally vulnerable $(III, IV, V)$. Whether this distinction matters in practice is a question we consider in the next section. More generally, the Figure vividly illustrates that information on current vulnerability alone is an insufficient basis for policy: one needs to know how vulnerability (or poverty) will change over time. Consider points $B$ and $C$. Households at these points have the same value for current vulnerability (with $V_0 = \widetilde{V}$) but (as indicated by the arrows) this equivalence applies only at $t = 0$. At all future times vulnerability $V_s$ $(s > 0)$ is greater for a household at $C$ than for a household at $B$. There is no justification for treating these two households equally just because they have the same value of $V_0$. Indeed Pareto efficiency requires differential treatment.

To see this consider the example of the Ramsey model where each household solves

$$\max_{\{c_t, k_{t+1}\}} E_0 \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{4}$$

subject to

$$\begin{aligned} c_t &= Af(k_t) + (1-\delta)k_t - k_{t+1} \\ \text{for } t &= 0, 1, 2, .. \text{ and } k_0, A \text{ given} \end{aligned}$$

where $c$ denotes consumption, $u$ the instantaneous utility function, $\beta$ a discount factor (where $0 < \beta = 1/(1+\rho) < 1$), and $\delta$ the depreciation rate. (We will use a variant of this model in our empirical example but recall that the Figure applies to a much wider class of conditional convergence models.) In this case households cannot trade in $k$ and there is no credit market. Assume that households have the same discount and depreciation rates but that they differ in productivity $A$. The relation between $A$ and $k^*$ is then given by the steady state equilibrium condition $Af'(k^*) = \rho + \delta$. This defines the $A(k^*)$ locus and on this locus the marginal productivity of capital equals $\rho + \delta$ for all households.

Choose points $B$ and $C$ in such a way that they are equidistant in terms of $k$ from the $A(k^*)$ locus. Now consider the following policy intervention. At time $t = 0$ assets are redistributed: agent $i$ receives a (positive or negative) transfer $\Delta_i = k_i^* - k_{0i}$ and has to pay an income tax $\Delta_i(\rho+\delta)$ for all $t$. By construction the net capital transfer is 0 ($\Delta_B + \Delta_C = 0$) and so is the net tax receipt. For $B$ the policy is equivalent to borrowing the amount needed to reach the steady state instantaneously at an interest rate $\rho + \delta$. Since without the policy the marginal productivity of capital always exceeds $\rho+\delta$ for $B$ the policy is welfare improving for this agent. Similarly, $C$ gains from the policy since it enables the agent to reach the steady state instantaneously in a way which is equivalent to lending out $k_{0C} - k_C^*$ at an "interest rate" which exceeds the marginal productivity of capital at all points along the path the agent would have chosen in the absence of the policy. Hence both agents gain from the policy. It follows that a policy of non-intervention (and hence non-discrimination) violates Pareto efficiency.

In the limit the government chooses amounts $\Delta_i$ so as to bring all agents on the $A(k^*)$ locus instantaneously.[7] This implies Pareto efficiency since all differences in the marginal productivity of capital are then eliminated. Note that the government policy substitutes for an asset (or, equivalently, a credit) market. If such a market existed agents would have reached the $A(k^*)$ locus instantaneously either by renting capital (in or out) or by buying capital on credit (or selling capital and investing the proceeds in a bank deposit).

The example shows that treating households $(B, C)$ with the same current vulnerability ($V_0 = \widetilde{V}$) equally (by non-intervention), would violate Pareto efficiency. The tax-cum-redistribution policy can establish efficiency (in effect by mimicking a credit or asset market) by moving households to the $A(k^*)$ locus. Once households are on that locus there is no scope left for Pareto improvements: capital has the same marginal productivity for all agents. On the locus households are in steady state equilibrium and in this unchanging situation a static poverty or vulnerability concept is an entirely appropriate welfare measure. The justification for a policy intervention based on such a measure (which would indicate that $C$ is worse off than $B$ reflecting the productivity differential between the two households) would be equity: there is no scope left for efficiency gains. Conversely, as long as there is scope for efficiency gains (that is if households are adjusting their assets so as

[7] If this involves a net transfer ($\Sigma_i k_i > 0$) then this is justified provided $\rho + \delta$ exceeds the cost of capital to the government.

to approach the $A(k^*)$ locus) then the use of static indicators is potentially misleading.

This is a fundamental dilemma. Either policy is based on simple welfare indicators which are essentially static and which do not require a particular microeconomic model. Unfortunately such indicators are justified only in steady state equilibrium when equity is the only reason for intervention. Or, the indicator is to be used as a basis for policy outside the steady state. In that case dynamics cannot be ignored and one requires a path (like our vulnerability indicator $V_s$ for $s = 0, 1, 2, ..$) rather than a point estimate of household welfare. In this case a policy maker would want to know whether a household (or group of households) can be expected to grow or decline in terms of $k$.[8] (Note that it is not always necessary to use a fully specified microeconomic growth model to derive such a path. It may well be that alternative, simpler methods provide adequate approximations. We investigate this in section 5.)

So far we have considered the deterministic case. If we introduce risk Figure 1 can still be used but its interpretation changes in two ways. First, there is no steady state; $k^*$ must now be interpreted as the mean of the ergodic distribution of the capital stock.[9] Secondly, the direction of asset changes (to the right for $B$, to the left for $C$) applies only in expectation. The same is true for the absence of asset changes: for points on the $A(k^*)$ locus assets do not change, but this is true only in expectation. A household which happens to be on the locus will stay on it only as long as it experiences no shocks. Any shock will trigger a process of adjustment and a change in the capital stock. The implication is dramatic: while a static measure is at least sometimes appropriate in the deterministic case, it is never appropriate in the case of (not fully insured) risk. Under full insurance the distinction between the deterministic and stochastic cases collapses and the conclusion is as before: the static measure is appropriate only if all households are on the $A(k^*)$ locus. Clearly, this very special case is of no practical interest; it is certainly not the situation for which vulnerability measures were designed.

How important is it to incorporate dynamics in the measurement of vunerability? As an example consider a special case of the Ramsey model, defined by $u(c) = \ln c$, $f(k) = Ak^\alpha$ where $0 < \alpha < 1$ and $\delta = 1$. The shock $\varepsilon$ is distributed lognormally with $E\varepsilon = 1$ and $\sigma^2$ denotes the variance of $\ln \varepsilon$.[10] This moodel has a closed form solution: the policy function for this case is $k_{t+1} = \alpha\beta A\varepsilon_k k_t^\alpha$ and consumption paths are given by $c_t = (1 - \alpha\beta)A\varepsilon_k k_t^\alpha$. Given the variance $\sigma^2$ we can calculate discounted expected utility.

We now compare in Table 1 the static Ligon and Schechter vulnerability measure and the dynamic extension given by equation (3). Recall that the Ligon-Schechter measure is $V = u(z) - Eu(c)$. Ligon and Schechter would interpret $Eu(c)$ as the mean of the distribution of consumption in the immediate future and would calculate it using either cross-section data or a short running

[8] In practice governments often discriminate between groups which differ in potential but not in current means. For example, means-tested social security is often not extended to university students.

[9] In Elbers *et al.* (2005) we derive this mean empirically and show how it is affected by changes in risk.

[10] This implies that $E \ln s = -\sigma^2/2$.

panel. This makes the measure myopic in paractice. We generalise the concept by considering as the $s$-period ahead Ligon-Schechter measure

$$V_s^{LS}(A_0, k_0) = u(z) - E_0 u(c_s).$$

In the Table we report this in the rows denoted LS. Our own measure for $T = \infty$

$$V_s(A_0, k_0) = E_0 \Sigma_{t=s}^{\infty} \beta^{t-s} [u(z) - u(c_t)]$$

evaluates utility over an infinite period. To make this comparable with the Ligon-Schechter measure we report in the Table (in the rows marked "this paper") $u(z) - (1-\beta) E_0 \Sigma_{t=s}^{\infty} \beta^{t-s} u(c_t)$. In the Table $B = \ln A_0 + \ln(\alpha\beta)^\alpha (1-\alpha\beta)^{1-\alpha}$. The expression $(B - \sigma^2/2)/(1-\alpha)$ is equal to $E_0 u(c_\infty)$. In the general case ($s = t$) the expression in brackets is a weighted average of future expected utility $E_0 u(c_\infty)$ and initial utility $u(c_0) = \ln c_0$. The two concepts then both measure expected discounted utility over an infinite horizon starting $s$ periods ahead. The crucial difference is that our measure uses the optimal values of consumption $c_s, c_{s+1}, ..$whereas the static Ligon-Schechter measure treats $c_s$ as a good proxy for consumption the period considered.

The two approaches can be seen to differ in the weights on the (expected utility) of $c_0$ and $c_\infty$. For example, the weight on initial utility is $\alpha^t (1-\beta)/(1-\alpha\beta)$ in our case and $\alpha^t$ (which is higher) in the Ligon-Schechter case. This indicates that the Ligon-Schechter measure overemphasises the role of current utility (or poverty). The difference is greatest for a myopic perspective ($s = 1$) and decreases with $s$. In the long run ($s = \infty$) the two measures coincide, as expected.

| | | |
|---|---|---|
| $s = 1$ | this paper | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha} \frac{1-\alpha}{1-\alpha\beta} + \frac{\alpha(1-\beta)}{1-\alpha\beta} \ln c_0]$ |
| | LS | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha}(1-\alpha) + \alpha \ln c_0]$ |
| $s = t$ | this paper | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha} \frac{1-\alpha\beta-\alpha^t(1-\beta)}{1-\alpha\beta} + \frac{\alpha^t(1-\beta)}{1-\alpha\beta} \ln c_0]$ |
| | LS | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha}(1-\alpha^t) + \alpha^t \ln c_0]$ |
| $s = \infty$ | this paper | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha}]$ |
| | LS | $u(z) - [\frac{B-\sigma^2/2}{1-\alpha}]$ |

**Table 1: Dynamic and Static Vulnerability Measures Compared**

# 4 An Empirical Example

In this section we investigate numerically to what extent the choice of policy instruments and the targeting on particular groups or individual households are affected by the length of the period considered by the policy maker.

Consider the special case of the Ramsey model discussed in the previous section with policy function $k_{t+1} = \alpha\beta A \varepsilon_k k_t^\alpha$. Income is defined by $y = A\varepsilon k^\alpha$. We choose the following parameters:

$A = \sqrt{5}, \alpha = 0.6, \beta = 0.9, \sigma = 0.25, k_0 = Ek_\infty = 1.56$ and a poverty line $z = 1.1$. We choose $\varepsilon_1 = 1$ in the first year (no shock).[11]

| | $W_1$ | $W_5$ | $C_1$ | $C_5$ | $U_1$ | $U_5$ | $H_1$ | $H_5$ |
|---|---|---|---|---|---|---|---|---|
| $y_0$ | 0.43 | 0.06 | 0.27 | 0.03 | 0.20 | 0.03 | -0.23 | -0.03 |
| $A$ | 9.27 | 10.48 | 0.60 | 1.46 | 0.43 | 0.98 | -0.47 | -0.90 |
| $-\sigma$ | 5.16 | 5.84 | 0.00 | 0.24 | 0.24 | 0.55 | -1.24 | -1.39 |

**Table 2: Impact of Three Types of Policies on Various Welfare Measures.**

Policies affect $y_0$, $A$ or $\sigma$. $W_s$ denotes the present value at $s$ of expected utility flows in accordance with equation (3); $C_s$ expected consumption at time $s$; $U_s$ expected utility in accordance with the Ligon-Schechter vulnerability measure; $H_s$ the expected headcount vulnerability measure. The cells give the partial derivative of the welfare measures with respect to the policy variables. They have been calculated from 10% increases in $k_0$ or $A$ or 10% *decreases* in $\sigma$.

In Table 2 we show how four different welfare measures (our own measure, $W$, based on an infinite utility stream, $C$, consumption, $U$, instantaneous utility and, $H$, the expected headcount vulnerability measure) are affected by three different policies: transfers (a change in $y_0$), productivity-enhancing measures (changes in $A$) or risk-reducing measures (changes in $\sigma$). We calculate the impact of these policies for two values of $s$: 1 and 5. As shown in Table 2, the effect of transfers is transient: transfers have very little impact on welfare measures five years ahead.[12] Conversely, the impact of productivity-enhancement increases with $s$. The increase in $A$ directly raises productivity permanently and in addition gives agents an incentive to invest more. Note that this effect is more pronounced for the "spot" measures $C$, $U$ and $H$ than for the forward looking $W$ measure.

The choice of policy instrument clearly depends on the marginal effects shown in Table 2 and the cost of the three policies. For example, a policy maker trying to maximise $W_5$ will prefer productivity enhancement over transfers provided:

$$\frac{1}{p_A}\frac{\partial W_5}{\partial A} > \frac{1}{p_{y_0}}\frac{\partial W_5}{\partial y_0}$$

or for

$$\frac{\partial W_5}{\partial A} \Big/ \frac{\partial W_5}{\partial y_0} > \frac{p_A}{p_{y_0}}.$$

Hence if we do not have data on the costs of the various policies, the LHS of this inequality, the relative marginal productivity, indicates the maximum of the relative price of that policy: for a

[11] By choosing $k_0 = Ek_\infty$ we bias the comparison in the direction of not finding a substantial difference between outcomes for $s = 1$ and $s = 5$.

[12] This is, of course, specific to the model used. In a poverty trap model transfers may well have permanent effects. Note however that there is as yet no convincing evidence of intertemporal poverty traps (e.g. Jalan and Ravalion, 2003).

higher price the numeraire policy of transfers would be better. Accordingly we show in Table 3 for each of the eight welfare measures the maximum relative price of the policy considered, treating the $y_0$-policy (transfers) as numeraire.

| | $W_1$ | $W_5$ | $C_1$ | $C_5$ | $U_1$ | $U_5$ | $H_1$ | $H_5$ |
|---|---|---|---|---|---|---|---|---|
| $A$ | 21.48 | 187.34 | 2.19 | 42.57 | 2.15 | 38.21 | 2.02 | 30.54 |
| $-\sigma$ | 11.97 | 104.39 | 0.00 | 6.94 | 1.20 | 21.29 | 5.32 | 47.19 |

**Table 3: Relative Effectiveness of Policies Changing $A$ or $\sigma$**

The rows are obtained by dividing the corresponding row in Table 2 by the row for $k_0$ in that Table. Relative effectiveness is measured as the maximum relative cost of the policy considered: at higher cost the numeraire policy transfers would be more effective.

The results are striking. For all welfare measures, the maximum relative prices rise dramatically (in many cases by a factor of around 10) when $s$ changes from 1 to 5. Hence there is a wide range of relative prices such that, for example, the $y_0$-policy would be chosen for a myopic measure ($s = 1$) while the $A$-policy would be prefered if the policy maker focused more on future benefits ($s = 5$). This suggests that if the policy maker is in fact concerned about long-run welfare but uses a myopic measure for convenience he may well choose the wrong policy. Clearly, myopic measures are biased against productivity enhancing or risk reducing policies and in favor of transfer policies.

We now consider a second way in which myopia may affect policy design: by inducing inappropriate targeting rather than distorting the choice of policy instrument. For this we use an existing microeconomic model of investment under uncertainty. In Elbers *et al.* (2005) we used an 18-year panel data set for smallholder households in Zimbabwe to estimate a stochastic version of the Ramsey model.

Figure 2 shows for five different combinations of the initial capital stock and total factor productivity how welfare ($W$) changes over time. We have calculated the expectation by averaging the value of $W$ over 100,000 simulated paths. The effect of heterogeneity in terms of $A$ and $k_0$ can be dramatic, as illustrated by the two paths in Figure 2 which initially have the lowest $W$ value. One of these households is very much more productive (an advantage which is initially offset by a lower value of $k$) and eventually reaches a very much higher welfare level.

Note that many of the paths actually cross each other. This implies that the ranking of households (in terms of welfare or vulnerability) changes over time. For example, the household which in Figure 2 initially has the highest value of $W$ ends up in third place: apparently its relatively low productivity was offset by a high initial value of $k$.

Whether such cross-overs are important depends on the distribution of households in ($A$, $k_0$) space. Figure 3 shows how the sample households are initially distributed. The contour lines show combinations of productivity and cattle for which household welfare ($W_0$) are the same. Note that

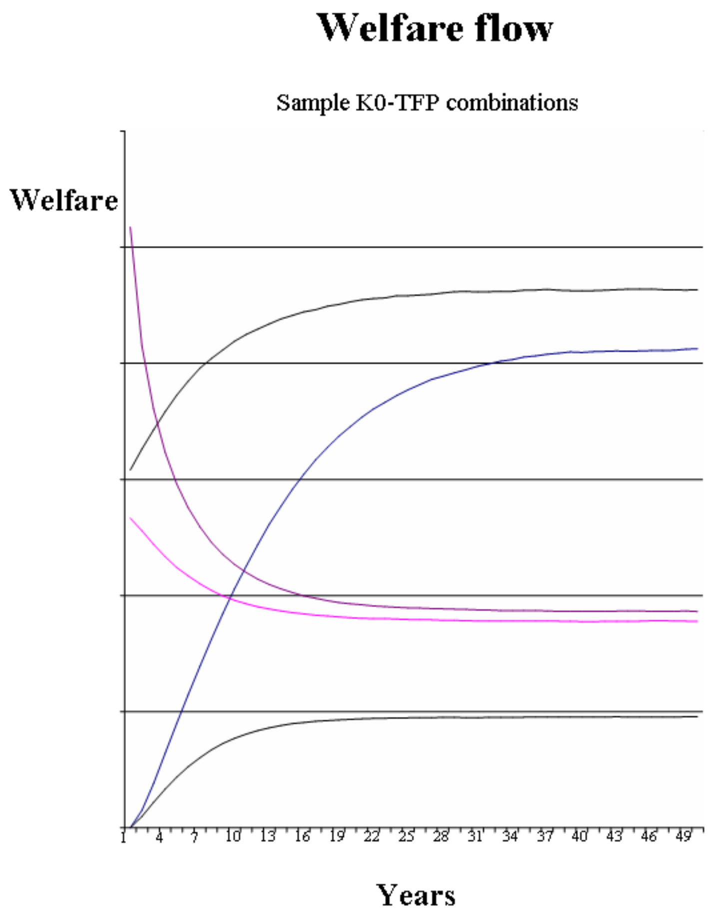


Figure 2: Welfare ($W$) for selected combinations of total factor productivity and initial capital.

these contours are very steep: $W_0$ is very sensitive to changes in initial asset ownership. (If we would take a longer horizon (say 5 years) the contours would become flatter, as in Figure 1.)

If we use a "headcount" concept then measuring vulnerability simply amounts to identifying those households with $W < u(z)/(1-\beta)$. If we were to use the official Zimbabwe poverty line then all households in our sample would be classified as vulnerable. For our present purpose of assessing how well existing vulnerability measures succeed in identifying the vulnerable, such a high value of

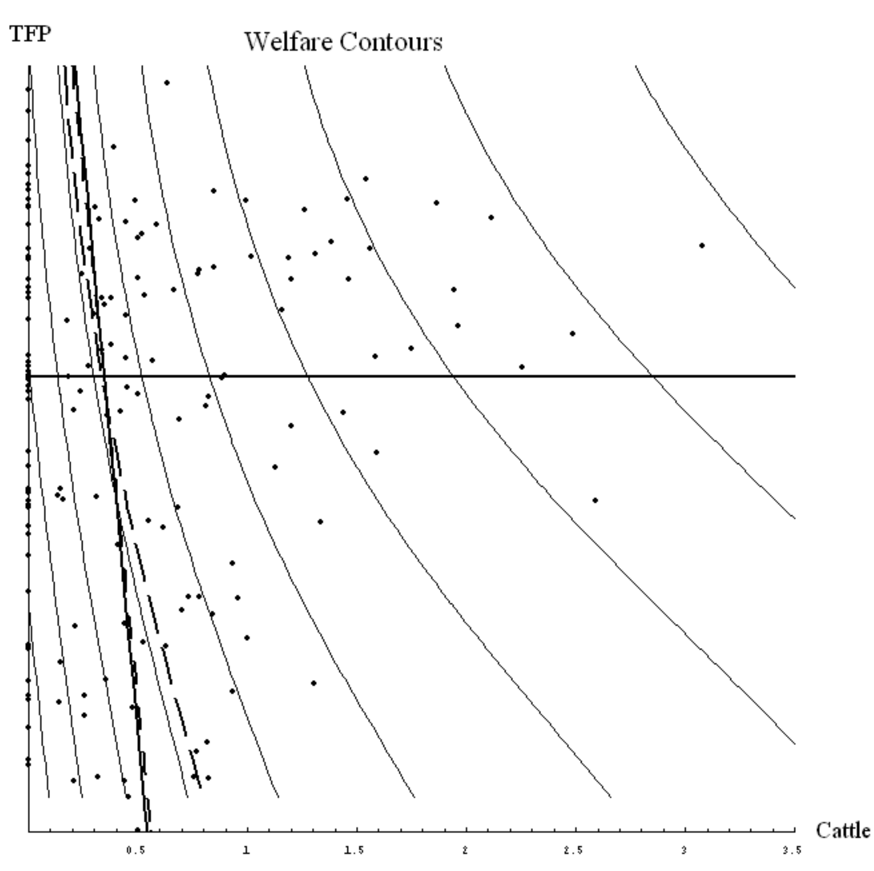


Figure 3: Classification of households as low-welfare (vulnerable) by various methods.

$z$ is not useful. We therefore choose a lower value of $z$, namely the value which classifies half of the sample as poor. In Figure 3 the line with large dashes separates the 50% worst off from the 50% best off: dots below this line represent households which are vulnerable at the chosen (obviously arbitrary) poverty line.

In terms of Figure 1 the distribution shown in Figure 3 has many households in areas $II$ (those who are currently but not structurally vulnerable) and in area $V$ (those who are structurally but not currently vulnerable). For this sample a focus on current vulnerability would be inappropriate if the government is concerned about long-run welfare.

# 5 Comparing Vulnerability Measures

In practice estimating a structural model of income dynamics may not be feasible. How far can we then get by using simpler, regression-based estimates?

One method used in the literature to assess vulnerability without relying on a structural model is to regress a household's consumption on household characteristics and measures of realized shocks (*e.g.* an illness in the household). The estimated coefficients can then be used to predict the household's poverty for a particular (essentially arbitrary) realization of shocks. Households with high predicted poverty are then considered as vulnerable conditional on these shocks.[13]

Theory implies a mapping from assets ($k$), shocks ($\varepsilon$), productivity determinants ($x$), and characteristics of the distribution of shocks ($\sigma$) to consumption ($c$):

$$c_{ht} = \xi(k_{ht}, \varepsilon_{ht}, x_{ht}, \sigma_{ht}) \tag{5}$$

where $h$ denotes a household. From this mapping one can derive appropriate vulnerability measures, such as our measure $W_0$, based on the household's expected discounted utility. (By including lagged values of $k$ and $\varepsilon$ estimates of $W_1, W_2, ..$can be obtained.) However, in practice vulnerability measures are not based on equation (5) but typically on regressions of $c_{ht}$ on $x_{ht}$ and possibly also on $\varepsilon_{ht}$ (e.g. Dercon and Krishnan, 2003). This approach is problematic in several ways.

First, by leaving out assets ($k$) the regression suffers from omitted variable bias. This could be serious: if two households are observed after being hit by a negative shock and if they are identical in all respects except for the level of assets then their consumption decisions may well be very different: the household with the higher $k$ can better afford to smooth consumption by using its assets. We would expect this to have a serious effect if the focus is on consumption in the near future (as in the $s = 1$ calculations above).

Secondly, omitted variable bias is also introduced by the exclusion from the regression of the shock characteristics $\sigma_{ht}$. A change in risk affects household behaviour both *ex ante* (*i.e.* the household will for the same values of $k$ and $\varepsilon$ decide on a different level of investment and consumption) and *ex post* (since the shocks are now drawn from a different distribution). If $\varepsilon$ is included in the regression but $\sigma$ is not, then this *ex post* effect can in principle be estimated but the *ex ante* effect will be missed. This is potentially serious: if one would like to estimate how much a policy-induced reduction in risk would contribute to welfare then one needs to have estimates of both effects.

Whether these objections are serious is an empirical matter. We investigate this with a series of experiments. We take the estimated Zimbabwe model and use it as the data generating process for a series of regressions (Table 4). In each case the data generated are for 1981.

The first regression relates consumption only to household-specific total factor productivity.[14] The performance of this regression is very poor. Clearly it cannot serve as a basis for identifying vulnerable households. The second regression includes shocks (income shochs $\varepsilon^y$ and asset shocks $\varepsilon^k$) as additional regressors.[15] This results in a substantial improvement of the fit. Finally, in the

[13] This method, used by Dercon and Krishnan (2000), does not take into account the probability of the realization considered and thereby fails to capture the extent to which the household is exposed to shocks. Clearly, the result cannot be interpreted as a measure of *expected* poverty since no information on the distribution of future consumption is used.

[14] In practice total factor productivity is not observed and must be inferred from household characteristics.

[15] The researcher would, of course, have at best partial information on these shocks.

last regression we also include the household's asset position (in terms of cattle). This leads to an excellent fit: $R^2 = .95$, in spite of the fact that the equation is *ad hoc* from a theoretical point of view.

**Table 4**

**Consumption regressions on simulated data**

| | TFP only | | TFP and shocks | | TFP, cattle, shocks | |
|---|---|---|---|---|---|---|
| | Coef. | s.e. | Coef. | s.e. | Coef. | s.e. |
| Constant | -19.64 | 17.5 | -20.84 | 15.6 | -4.61 | 0.501 |
| TFP | 8.474 | 7.22 | 7.026 | 6.42 | 0.522 | 0.094 |
| $\text{TFP}^2$ | -0.760 | 0.737 | -0.627 | 0.656 | | |
| Cattle | | | | | 3.485 | 0.077 |
| $s^y$ | | | 4.076 | 1.402 | 3.122 | 0.373 |
| $s^k$ | | | 0.755 | 1.305 | 0.262 | 0.347 |
| $R^2$ | 0.050 | | 0.258 | | 0.948 | |
| Dependent variable is simulated after-shock 1981 consumption | | | | | | |

We now consider how such regressions can be used to identify vulnerable households. If vulnerability was measured on the basis of the first regression, *i.e.* on the basis of total factor productivity, and if in addition the researcher knew that 50% of the population was vulnerable then he would identify vulnerable households as those below the bold horizontal line in Figure 3. Clearly many vulnerable households would not be identified as such and vice versa. This is shown in Table 5 which shows that almost 40% of the households are misclassified by this regression. (The error would be larger if, realistically, the researcher did not know how many households were poor and if he could observe some of the household characteristics which determine productivity but not productivity itself.) This suggests that regression-based estimates which measure vulnerability on the basis of observable proxies for total factor productivity may be very inaccurate.

The two steeper lines in Figure 3 correspond to regressions with cattle ownership as the only explanatory variable (solid line) or with cattle ownership and shocks as the regressors (short dashes). Very few households are misclassified by these regressions. (The fact that the contours corresponding to these two regression are steeper than the true iso-vulnerability locus reflects the fact that the model also takes into account the long-run effects of total factor productivity.) Indeed, as shown in Table 5, in either case only two households are misclassified. This suggests that in vulnerability analysis the perfect need not be the enemy of the good. When the panel data needed to implement a structural model such as the stochastic Ramsey model are not available, then it is still possible to achieve a very good approximation on the basis of cross-section data, provided asset data are included in the regression.

| Table 5 | | |
| --- | --- | --- |
| **Classifying the 50% poorest households.** | | |
| **using regression models** | | |
| Model | TFP only | TFP, cattle |
| | | and shocks |
| Correct poor | 48 | 78 |
| Correct non-poor | 48 | 78 |
| False poor | 31 | 1 |
| False non-poor | 31 | 1 |
| Total | 158 | 158 |

# 6 Conclusion

In the design of pro-poor interventions policy makers are concerned with their impact on welfare at some future time. However, current poverty may be a poor indicator of future welfare, for two reasons: households are exposed to risk and they engage in accumulation. Under risk currently non-poor can become poor as a result of negative shocks and, conversely, households may escape from poverty as a result of positive shocks. Since the empirical literature shows that households in developing countries face substantial risk this presents a problem for policy design. To some extent the vulnerability literature has attempted to address this issue by decomposing welfare into a deterministic and a risk-related component but typically the literature has ignored income dynamics as a result of asset accumulation. In this paper we focus on the implications of such dynamics for policy design.

If dynamics are taken into account this may affect policy design in two ways. First, what constitutes an appropriate policy depends on whether or not one adopts a dynamic perspective. We use an analytical growth model to illustrate this for three types of interventions: transfers, policies that raise productivity or reduce risk. We show that using myopic measures (such as the existing poverty and vulnerability measures) biases policy design in favor of transfers.

Secondly, the composition of the group of low-welfare households may change dramatically over time especially because of inter-household differences in productivity: high-productivity households are much more successful in overcoming negative shocks. In this situation targeting on the basis of current welfare indicators might be inefficient. We showed, using panel data for rural households in Zimbabwe, that this issue is empirically important.

Taking dynamics into account does not necessarily involve estimating a structural dynamic model. We have shown for the Zimbabwe example that simpler methods (using consumption regressions) can be an adequate substitute.

It is dangerous to ignore dynamics in policy design: it may undervalue the scope for policies aimed at structural changes and focus interventions on the wrong groups.

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