LOWER PARTIAL MOMENTS AS A MEASURE OF VULNERABILITY TO POVERTY IN CAMEROON

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Discussion Paper No. 434

November 2009

Abstract

In this paper the class of Lower Partial Moments (LPMs) is used for measuring vulnerability as downside risk of household income in rural Cameroon. This class of established and coherent risk measures has been shown to meet a number of desirable properties. Among others, the LPMs fulfill the focus axiom, and for order greater than zero they are in harmony with expected utility theory under the weak assumption of risk aversion. Through combining the vulnerability measure with a portfolio approach it is possible to distinguish different livelihood systems for which the poverty and vulnerability measures are the explicit result of stochastic distributions of single activities in the households' portfolio and their covariance structure. In particular we consider the four major income generating activities in the study area: Sorghum, millet and rice production, and fishing. The results suggest that in the study area fishermen are less affected by adverse effects on income than other livelihood systems, while rice growers are the poorest and most vulnerable. It is also shown that rice and millet growers are suffering from chronic poverty, while transient poverty is more prevalent among the group of sorghum growers and fishermen. This implication is further confirmed by assuming a moving target equal to the mean portfolio income for the calculation of LPMs. The results of the scenario analysis suggest that policy interventions aiming at a reduction of the covariation structure between income flows from different activities are quite promising.

Keywords: Vulnerability as expected poverty, Lower Partial Moments, portfolio theory, diversification, Sub Saharan Africa

JEL Classification: I32, O13, G11, G32

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Introduction

Research on poverty has more and more acknowledged that uncertainty and risk need to be considered in measuring the welfare position of households. In particular, the concept of vulnerability has recently become quite prominent in theoretical and empirical research. Inspired by Ravallion (1988), vulnerability is mostly defined as expected poverty (V^{EP}). Methodologically, V^{EP} measures extend the static Foster-Greer-Thorbecke (FGT) poverty measures to make predictions on the probability of being poor in the future. Some examples of this approach can be found in Pritchett et al. (2000), Chaudhuri et al. (2002), Christiansen and Subbarao (2005), Kamanou and Morduch (2001), Günther and Hattgen (2006, 2009), Günther and Maier (2008), Béné (2009), and Chiwaula et al. (2009).

Although some authors (e.g. Ligon and Schechter 2003, Calvo and Dercon 2005) have been arguing that the V^{EP} measure seems to be ill-suited to represent household risk attitudes, it fulfills many desirable properties which are also inherent to the FGT poverty measures, including symmetry, replication invariance, subgroup consistency and decomposability (Foster et al. 1984). In particular, the V^{EP} is fulfilling the focus axiom, which states that vulnerability measures should focus on downside risk only, since favorable outcomes in good states of the world do not necessarily ensure lower vulnerability (Calvo and Dercon 2005).

To address the critique of implicit risk attitude assumptions of the V^{EP}, we suggest that the general concept of vulnerability, defined as an ex-ante risk measure based on stochastic welfare distributions, is not different from risk analysis concepts as they have been widely applied in the finance world since the 1950s, for example to pricing, hedging, portfolio optimization or capital allocation. In particular, we propose the use of the Lower Partial Moments (LPMs) as a measure of vulnerability as expected poverty. Without explicitly referring to the LPMs, this approach has also been applied in a slightly modified specification by Christiaensen and Subbarao (2005). The LPMs are one class of coherent measures of risk, introduced by Fishburn (1977) and Bawa (1975, 1978), which are measures of downside or shortfall risk, where only negative deviations from a target outcome are taken into consideration. In contrast to symmetrical risk measures, the LPMs capture the common notion of risk as a negative, undesired characteristic of an alternative (Brogan and Stidham 2005, Albrecht and Maurer 2002, Unser 2000), which is also in line with the focus axiom. Further, LPMs have a number of convenient characteristics. First, they are consistent to the ordering of distributions derived from stochastic dominance rules and utility maximization for risk-averse households. Second, LPMs are coherent risk measures, satisfying the axioms of subadditivity, positive homogeneity, monotonicity and translation invariance (Artzner et al. 1999, Cheng et al. 2004, Acerbi et al. 2001, Acerbi and Tasche 2002, Peracci and Tanase 2008). This set of axioms has been widely accepted and regarded as a landmark in the field of risk theory (Cheng et al. 2004). Third, analogous to the FGT measures, the LPMs are additively decomposable, so that vulnerability can be measured not only on individual or household level, but also be aggregated for different population groups. And finally, LPMs are intuitively interpretable, an attribute that is of eminent importance in view of policy advise. Analogous to the class of FGT poverty indicators, the LPMs not only identify the vulnerable, but also show how pronounced vulnerability is in terms of consumption or income under downside risk.

A related question that we also address here is, how to derive a stochastic distribution of welfare, particularly income. This issue is critical for vulnerability assessment, since vulnerability measures are always based on the estimated mean and variance of a welfare indicator. However, panel data of sufficient length are virtually not existing for most developing countries. Thus, some authors have suggested to apply econometric models such as the 3-step FGLS model (Just and Pope 1979), which assumes that intertemporal variation is reflected in the cross-sectional variation of the error term. A possible alternative presented here is a simple risk assessment method, which is fully sufficient do derive an outcome-activity matrix as suggested by portfolio theory (Witt and Waibel 2009).

This paper is organized as follows: In the next section we will briefly outline the portfolio theory which is used to calculate stochastic income distribution parameters, and also introduce the LPM risk measure and discuss its properties. The remaining part of the paper presents an empirical application on data from 238 rural households in Northern Cameroon in 2008. We close with a short conclusion and suggestions for further research.

Portfolio theory and LPMs

To arrive at the stochastic distribution of household income we apply the general portfolio theory developed by Markowitz (1952) which has its analytical foundation in Von Neumann and Morgenstern's expected utility theory under uncertainty. Portfolio theory has been applied on agricultural decision problems since the 1970s. Attention in agricultural economics has especially concentrated on optimization methods with mathematical programming techniques (and linear capital and technical constraints) to model farm decision problems and to find the portfolio of farming activities which maximizes expected utility (EU) under risk (see for example Hazell 1971, Tauer 1983, Teague et al. 1995, Chen and Baker 1974, Tew et al. 1992, Scott and Baker 1972).

The stochastic distribution of farm income is defined as a function of the distributions of single income-generating activities and subjective probabilities of different states of the world (see Witt and Waibel 2009 for a detailed description). Denote $i = (1,\ldots,I)$ the income generating activities of a household, and $s = (1,\ldots,S)$ the set of states of nature, and assume it is finite. Then *E(I$_i$)* and *V(I$_i$)* are functions of the probabilities γ_s, yield $Y_{i,s}$ of crop *i* at state *s*, and price $P_{i,s}$. More precisely:

$$E[I_i] = \sum_{s=1}^{S} \gamma_s \cdot Y_{i,s} \cdot P_{i,s} \,,$$

$$V[I_i] = \sum_{s=1}^{S} \gamma_s \cdot \left(Y_{i,s} \cdot P_{i,s} - E[I_i]\right)^2 \text{, and}$$

$$Cov[I_i, I_j] = \sum_{s=1}^{S} \gamma_s \cdot \left(Y_{i,s} \cdot P_{i,s} - E[I_i]\right) \cdot \left(Y_{j,s} \cdot P_{j,s} - E[I_j]\right) \text{ for all } i \neq j \in n$$

In the lines of financial asset portfolios, the mean and variance of the household income portfolio is then calculated as a function of these distribution parameters, weighted by the share of labor allocated to the respective activity:

$$E[I_{PF}] = f(\vec{w}_i, E[I_i | \gamma_k, Y_k, P_k]) = \sum_{i=1}^{n} w_i E[I_i] = \sum_{k=1}^{K} \sum_{i=1}^{n} w_i \gamma_k Y_k P_k$$

$$V[I_{PF}] = f(\vec{w}_i, V[I_i], Cov[I_{i,j}]) = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}^2$$

Thus, the two moments of the distribution of portfolio income describe the stochastic nature of production, depending on the uncertain outcomes of the single activities, and the covariance structure.

Departing from the early portfolio models which were simply based on variance (or standard deviation) as risk measure, it has been argued that the variance of an outcome variable is a dubious measure of risk, since making decisions on production or investment in a risky environment is mostly concerned with expected losses rather than expected gains. Due to the symmetrical nature of variance, this measure assigns the same weight to positive as to negative deviations from the expected value and hence does not capture the common notion of risk as a negative, undesired characteristic of an alternative, nor does it account for fat tails of the underlying distribution (Cheng et al 2004, Jarrow and Zhao 2006, Brogan and Stidham 2008, Albrecht and Maurer 2002, Unser 2000). An experimental study by Unser (2000) shows that symmetrical risk measures can be clearly dismissed in favor of shortfall measures like LPMs. Hence, some recent risk assessment approaches have been using Lower Partial Moments (LPM) to describe investments in financial assets (for example Nawrocki 1999, Schubert and Bouza 2004, Ballestro et al. 2007). Qui et al. (2001), Liu et al. (2008) and Webby et al. (2008) applied the framework of partial moments (upper partial moments or the Conditional Value-at-Risk, which is a special case of the LPM measures) on agricultural production decisions in an uncertain environment.

The Lower Partial Moment of the lth order is defined as:

$LPM_l(x,u) := E\left[((x-u)^+)^l\right] = \int_{-\infty}^{x}(x-u)^l f(u)du$, where x is a target separating gains and losses, u is a random variable (e.g. income) and $f(.)$ is a probability distribution function. The reference point x can be specified as a fixed target, e.g. a given income poverty line which applies to all households equally, or as a moving target, i.e. the target is not fixed but depends on the household specific distribution of the random variable (Brogan and Stidham 2008). Schubert (1996) shows that for a normally distributed variable, the LPM of the lth order can be computed as:

$$LPM_l = \frac{1}{\sqrt{2\pi\sigma}}\int_{-\infty}^{x}(x-u)^l \cdot e^{\frac{-(u-\mu)^2}{2\sigma^2}} du$$

Setting *l=0* yields the target shortfall probability[1]. The LPM of the order *l=1* is the target shortfall mean, often also called expected loss or expected shortfall. The LPM of order *l*=2 is known as the target shortfall variance or target semi-variance. In this case risk is measured by squared deviations below the target *x*.

Applying LPMs as a measure of income risk is appealing in that there is no need to explicitly assume an arbitrary risk aversion parameter since LPMs are consistent to the ordering of distributions derived from stochastic dominance rules and utility maximization for risk-averse households (Bawa and Lindenberg 1977). Unser (2000) shows that for F to be preferred to G it is necessary and sufficient that:

- For all $u(x) \in U_1 \equiv \{u(x) | u'(x) > 0\} := LPM_{0,F} \leq LPM_{0,G} \Leftrightarrow FSD$
- For all $u(x) \in U_2 \equiv \{u(x) | u'(x) > 0 \, and \, u''(x) < 0\} := LPM_{1,F} \leq LPM_{1,G} \Leftrightarrow SSD$
- For all $u(x) \in U_3 \equiv \{u(x) | u'(x) > 0; u''(x) < 0 \, and \, u'''(x) > 0\} := LPM_{2,F} \leq LPM_{2,G} \Leftrightarrow TSD$.

Hence, the concerns raised concerning the implicit assumption of unrealistic risk attitudes by V^{EP} measures are invalid for the class LPMs. LPM_1 is consistent with the HARA, and LPM_2 is consistent with the DARA class of utility functions (Persson 2000).

Given the assumption of normal distribution, LPMs can be easily computed by creating a standardized variable $m = \frac{x - \mu}{\sigma}$, so that:

- $LPM_0 = F(x) = \Phi(m)$
- $LPM_1 = (x - \mu)\Phi(m) + \sigma\varphi(m)$
- $LPM_2 = \left[(x - \mu)^2 + \sigma^2\right]\Phi(m) + \sigma(x - \mu)\varphi(m)$.

Analogous to the FGT poverty indicators, which are defined as $P_\alpha(z) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{z - y_i^*}{z}\right)^\alpha$, LPMs can be used to implement the risk dimension in measuring welfare (Table 1).

Table 1: Analogy between FGT and LPM indicators

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[1] The LPM_0 is equivalent to the definition of vulnerability as the probability to be poor (e.g. Chaudhuri et al. 2002). Under the assumption of normal distribution, vulnerability is defined as: $v_{ht} = \Pr(u \leq x) = \Phi\left[\frac{(x - \hat{E}(u))}{\sqrt{\hat{V}(u)}}\right]$.

FGT			LPM		
Order	Indicator	Interpretation	Order	Indicator	Interpretation
α=0	Poverty incidence	Headcount ratio	l=0	Shortfall probability	Probability that expected income will be lower than target
α=1	Poverty depth	Poverty Gap Index = average shortfall of living standards from the poverty line	l=1	Expected Shortfall	Expected negative deviation from target
α=2	Poverty severity	Weighted sum of poverty gaps (e.g. Squared Poverty Gap Index)	l=2	Target Semi-Variance	Squared deviations below the target.

Source: own illustration

Setting the target x equal to a given poverty line, FGT poverty measures and LPMs can be directly compared. A potential problem with the safety-first criterion is that the definition of the subsistence minimum is essentially arbitrary (Alderman and Paxson 1992). The same concern is also often raised regarding the use of a poverty line for general economic poverty analysis. A possible solution is the use of a moving target $x = E[u]$ (Brogan and Stidham 2008, Povell 2009). In the case of a normal distribution LPM_0 would be 0.5 for all cases. The LPM_1 however would reflect the risk of loss relative to the respective household's living standard and not to an arbitrary poverty line. It seems reasonable to assume that the overall objective of an economic agent is to not fall below the expected or mean income, i.e. to improve or at least to maintain the habitual living standard. The assumption of a poverty line may do injustice to households that are relatively better off, but still face a high risk of losses due to some stochastic events. Nonetheless, for the purpose of this paper we assume a fixed income poverty line, which we define as 50% of the average portfolio income of the sample. This assumption still permits to derive risk measures for all households irrespective of their classification as poor or non-poor applying the FGT measure.

Study site and data collection

The approach proposed here has been applied on data that were collected in the Logone floodplain in the Far-North province of Cameroon in May 2008. Ecologically, this area is characterized by Sudano-Sahelian climate and vegetation. The livelihoods of the people living in this area (mainly subsistence agriculture and small-scale fisheries) are heavily dependent on natural resources and climate conditions. Due to the increasing aridification and increased frequency of droughts and floods, agricultural production in this area has been shifting to hardy plants with relatively low water requirements and a short growing season, such as sorghum and millet. Fishing is a major activity for many households in terms of nutrient supply and income generation and is carried out by almost every conceivable means.

A two-step weighted random sampling procedure was employed to identify the sample households. Data were collected in May 2008. The final sample size after data entry and cleaning is 238 households.

For the collection of data on crop yields, prices, and income flows from fishing, we applied a visual impact method (VIM), based on Hardacker et al. (1997). VIM is an approach to elicit subjective probabilities for stochastic outcomes, as long as the number of possible outcomes is not too great. In our case we delimited the states of the world to S=3, i.e. "bad year", "normal year" and "good year". In a risk assessment interview, three rectangles were drawn on the soil, designating the three states of the world. After enquiring about the household's main income generating activity, each respondent (usually the household head) was then asked to report how often out of the past ten years (covering the period 1998-2008) they had encountered a bad, normal or good year in this primary activity. For this exercise they were given 10 stones and asked to allocate them among the three rectangles. The relative number of stones in each state of the world represents the subjective probability of facing a certain climatic event (either normal, adverse or favorable). Referring to this probability distribution, several questions followed concerning the average yield levels for the primary crop (as well as for all complementary activities carried out by the household) in each state of the world. The data that was generated through this exercise was used to derive probability density functions for each activity, as well as the correlation coefficients between the activities.

A limitation of this approach is that it is not possible to cover the tails of the yield distributions for complementary activities, since the primary activity is taken as a reference. However, in the presence of data limitations this constraint had to be accepted for the benefit of capturing the correlation structure between different activities.

The labor input data that was used for portfolio analysis has been reported in mandays for the year 2007, covering all seasons. This data has been used as an approximation for the average labor input.

Results

Overall, the results show similar behavior of the poverty (FGT) and vulnerability (LPM) measures, which is in line with the majority of research findings. Vulnerability is nonetheless found to be higher than poverty over the whole range of indicators. This is largely due to the fact that we consider downside risk in the analysis on dynamic poverty. To test for the sensibility of results to the definition of the poverty line, a sensitivity analysis has been conducted (Table 2). Taking the average portfolio income of 354USD, the poverty line is shifted upwards by 10 percentage points from 10 to 90 percent of the mean income. To account for the fact that the expected shortfall is computed for all households, while the poverty gap only holds for the poor household, we present both indicators for the group of poor households, which increases from almost zero to over 54 percent of the sampled households. The results show that the expected shortfall (LPM_1) is in all cases greater than the average poverty gap (FGT_1). Hence, the definition of the poverty line is not supposed to alter the ordering of households by applying poverty and vulnerability measures. In the following we therefore apply a relative poverty line of 50 percent of the mean income for comparison purposes.

Table 2: Sensitivity analysis of FGT and LPM indicators to an increase of the poverty line

Threshold of mean income	Poverty line [PPP USD]	Poverty head count ratio	Average poverty gap [PPP USD] (poor only)	Shortfall probability	Expected Shortfall [PPP USD] (poor only)
0.1	35.4	0.00	14.87	0.03	14.87
0.2	70.8	0.06	11.76	0.09	21.94
0.3	106.2	0.14	32.25	0.17	37.54
0.4	141.6	0.20	46.05	0.24	56.06
0.5	**177**	**0.28**	**67.48**	**0.31**	**70.99**
0.6	212.4	0.36	76.05	0.38	89.14
0.7	247.8	0.40	94.77	0.44	114.04
0.8	283.2	0.47	107.45	0.50	131.22
0.9	318.6	0.54	122.58	0.55	148.51

Source: own data

Households have been categorized into four livelihood groups, i.e. sorghum, millet and rice farmers, or fishermen, if the major part of household labor is allocated to the respective activity. Table 3 presents the moments of the income distribution, i.e. the average annual portfolio income per capita and the standard deviation of income, as well as the FGT poverty indicators and LPM vulnerability indicators for each group.

Table 3: Moments of portfolio income distribution and poverty line

Poor			Sorghum growers	Millet growers	Rice growers	Fishermen	Total
N			9	10	45	3	67
Mean portfolio income			129.99	126.31	101.60	111.37	109.54
Standard deviation of portfolio income			41.05	32.34	30.54	40.12	32.65
FGT poverty indicators	α=0	Poverty head count ratio	1.00	1.00	1.00	1.00	1.00
	α=1	Average poverty gap	30.03	50.69	60.44	35.63	67.48
	α=2	Squared poverty gap	3675.36	4016.23	7311.49	6288.17	6285.40
Lower partial moments	l=0	Shortfall probability	0.80	0.85	0.91	0.84	0.88
	l=1	Expected Shortfall	53.42	54.29	78.21	71.01	70.99
	l=2	Target Semi-Variance	5305.84	5084.39	8425.94	7619.93	7471.99

Non-Poor			Sorghum growers	Millet growers	Rice growers	Fishermen	Total
N			82	17	45	27	171
Mean portfolio income			438.59	364.09	393.77	631.38	449.83
Standard deviation of portfolio income			163.52	91.61	77.97	191.20	138.23
Lower partial moments	l=0	Shortfall probability	0.11	0.11	0.07	0.06	0.09
	l=1	Expected Shortfall	10.28	4.22	3.24	4.68	6.94
	l=2	Target Semi-Variance	2526.48	422.47	301.52	669.11	1438.53

Poor and Non-poor			Sorghum growers	Millet growers	Rice growers	Fishermen	Total
N			91	27	90	30	238
Mean portfolio income			408.07	276.02	247.69	579.38	354.04
Standard deviation of portfolio income			151.41	69.66	54.26	176.10	108.51
FGT poverty indicators	α=0	Poverty head count ratio	0.10	0.37	0.50	0.10	0.28
	α=1	Average poverty gap	4.65	18.78	37.71	6.56	19.00
	α=2	Squared poverty gap	363.50	1487.49	3655.74	628.82	1769.42
Lower partial moments	l=0	Shortfall probability	0.18	0.38	0.49	0.14	0.31
	l=1	Expected Shortfall	14.54	22.76	40.73	11.31	24.97
	l=2	Target Semi-Variance	2801.36	2149.11	4363.73	1364.19	3137.02

Source: own data

We find that 28 percent of the sampled farmers are poor[2] with an average poverty gap of 64.5USD. Poverty however is unequally distributed among the livelihood groups. While only about 10 percent of sorghum growers and fishermen have a (time-mean) income below the poverty line, poverty incidence among millet and rice growers is 37 and 50 percent, respectively. The same pattern is observed in terms of the average poverty gap, where rice growers have the largest poverty gap with 60.44USD per capita among the poor and 37.71USD per capita for the whole sample.

In terms of vulnerability, the average shortfall probability is 31 percent with an expected shortfall of about 71USD. However, vulnerability comparison between the poor and the non-poor reveals that poor fishermen are second in terms of the expected shortfall with 71USD, while the loss risk for poor sorghum and millet growers is much lower with about 54USD. This indicates that poor farmers growing millet and sorghum as their primary crop are less liable to production risk than fishermen. Compared to the group of non-poor farmers, the results become substantially different. In this group sorghum growers are the most vulnerable (with 11 percent average shortfall probability and 10.3USD expected shortfall), and rice farmers are the least vulnerable in terms of expected shortfall. While non-poor fishermen generate the highest income (631.4USD) the variability of income is comparatively high and makes these households more vulnerable to risk. To the contrary, non-poor rice farmers have a relatively low income, but the standard deviation of income results in low vulnerability levels. Nevertheless, due to the high proportion of poor within the group of rice growers, average poverty and vulnerability incidence is highest for this livelihood group.

If we interpret the FGT measure as chronic poverty, it can be concluded that rice and millet farmers are suffering from chronic poverty, while transient poverty is more prevalent among the group of sorghum farmers and fishermen. Overall, the per capita values of the LPMs (i.e. including poor and non-poor households) show that fishermen are clearly dominating other livelihood strategies by second as well as third order stochastic dominance. Rice farmers are dominated by all other groups, while there is a change in ordering for sorghum and millet growers, by LPM_1 and LPM_2, which implies that, although the average expected shortfall

[2] Since we use the time-mean household income, the poverty measures can be interpreted in the sense of Jalan and Ravallion's (2000) chronic poverty measure.

is higher for millet growers, the LPM_2 values indicate that the inequality of income distribution is expected to be higher for sorghum growers and the relatively high variation makes these households more vulnerable to poverty even if their time-mean portfolio income lies above the poverty line.

The vulnerability results for the group on non-poor (or transiently poor) households already show that downside risk is an issue for all households irrespective of their position around the poverty line. As we have argued before, a reasonable assumption for the analysis of downside risk could be that households seek to maintain the habitual living standard, i.e. the expected shortfall could also be analyzed with respect to the mean portfolio income instead of a fixed poverty line. Thus, comparing LPMs with fixed and moving target we find that the expected negative deviation from the poverty line is decreasing in income, while with a moving target, the expected loss is increasing in income, i.e. households with a higher portfolio income face on average a larger income risk (Figure 1).

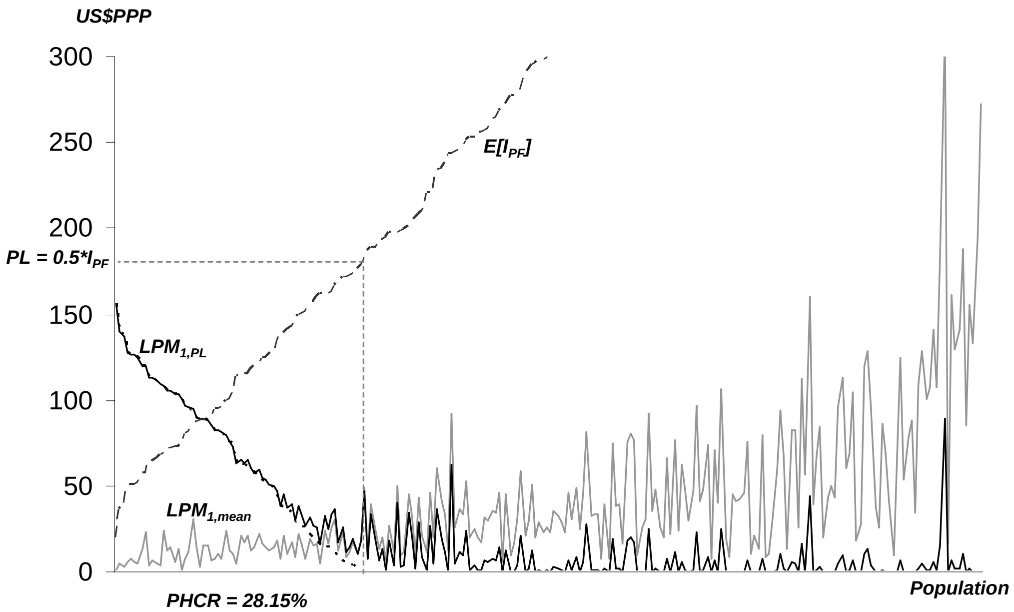

Figure 1: Distribution of first order LPM (expected shortfall) with fixed and moving target

Source: own data

For the proportion of households below the poverty line, expected shortfall (*$LPM_{1,PL}$*) and poverty gap are moving very closely together. For the moving target (*$LPM_{1,mean}$*), results show that the risk-income ratio (where risk is represented by expected shortfall) is on average constant (about 0.122) over the whole range of the income distribution.

Splitting the expected shortfall (*$LPM_{1,PL}$* and *$LPM_{1,mean}$*) by livelihood group, we find remarkable differences in risk, depending on the definition of the target (Table 4). In general, for the poor households, expected shortfall is significantly lower if the target x is defined as *E[u]*, the time mean income, as compared to the poverty line target. This result is consistent with expectations, because mean income for the poor lies below the poverty line per definition. To the contrary, *$LPM_{1,mean}$* is significantly higher than *$LPM_{1,PL}$* for the non-poor, as indicated by Figure 1.

Table 4: First order LPM (expected shortfall) with fixed and moving target, by poverty and livelihood group

		Sorghum growers	Millet growers	Rice growers	Fishermen	Total
Poor						
N		9	10	45	3	67
Mean portfolio income		129.99	126.31	101.60	111.37	109.54
Standard deviation of portfolio income		41.05	32.34	30.54	40.12	32.65
Expected Shortfall	PL	53.42	54.29	78.21	71.01	70.99
	E[u]	16.38**	12.90***	12.18***	16.01	13.03
Non-Poor						
N		82	17	45	27	171
Mean portfolio income		438.59	364.09	393.77	631.38	449.83
Standard deviation of portfolio income		163.52	91.61	77.97	191.20	138.23
Expected Shortfall	PL	10.28	4.22	3.24	4.68	6.94
	E[u]	65.23***	36.55***	31.11***	76.28***	55.14
Poor and Non-poor						
N		91	27	90	30	238
Mean portfolio income		408.07	276.02	247.69	579.38	354.04
Standard deviation of portfolio income		151.41	69.66	54.26	176.10	108.51
Expected Shortfall	PL	14.54	22.76	40.73	11.31	24.97
	E[u]	60.40***	27.79	21.64***	70.25***	43.29

Source: own data
Note: *, **, *** indicate significance levels of difference in mean at 0.1, 0.5 and 0.01, respectively (paired T-test)

A comparison between livelihood groups shows that the ordering of distributions changes dramatically if the target is set as the time-mean income of the household. Now, rice farmers are dominating other groups by second order stochastic dominance for *$LPM_{1,mean}$*, i.e. rice farmers are less liable to adverse production conditions in terms of negative deviations from the usual living standard than other livelihood groups. While the difference for millet farmers (poor and non-poor) is not significant, rice farmers show even a reduction in vulnerability if the target is defined at the time-mean income. To the contrary, we find that sorghum farmers and fishermen are now most affected by negative events and hence most likely to fall below the target.

These results show that fishermen are able to generate higher incomes, which comes at the cost of high variation in income. While these households are thus less vulnerable to poverty (if poverty is defined at a fixed threshold, below which households are considered as poor), they nonetheless face a high risk of not attaining the time-mean income. Transient poverty however is nonetheless a non-negligible issue for fishery-dependent households. In order to counteract the high income variability, fishermen and sorghum farmers may resort to livestock as a form of informal savings and credit market. However, while this may be true for sorghum farmers, fishermen are found to be least endowed with livestock The value of livestock (including small ruminants) as reported by respondents is 3339, 2352, 1603 and 940 USD for sorghum, millet, rice farmers and fishermen, respectively. That result implies that fishermen may need different policy interventions (e.g. establishing functioning credit markets) than agriculture oriented households.

Scenario analysis

In order to test, how certain hypothetical interventions would affect income and risk, a scenario analysis has been conducted based on research findings and policy propositions, which are presented below.

Following forecasts on climate change it can be assumed that extreme events, such as flooding and drought will occur more often in the future. As exemplified by McCarl et al. (2008) higher variance in climate conditions tends to lower average crop yield and increase the variability of crop yield distributions. In combination with ongoing aridification and desertification of the study area, we can presume that the probabilities of extreme events will increase in the future. To simulate such changes on the portfolio outcomes, we assume a shift of probabilities from a “normal” year to “good” and “bad” years in our subjective probabilities distribution by 50% respectively. The first scenario therefore shows the trend in income and risk changes due to climate change.

Addressing climate risks, autonomous adaptation strategies, such as changing crop varieties, altering the timing or location of cropping activities, or diversification, are highly relevant for smallholder farmers (IFAD 2008). Certainly, in the context of agricultural production under water stress and increasing climate variability, a promising adaptation method is improved crop and soil water management (Giorgis et al. 2006, Molua 2008). According to Ellis (1993), perhaps the most obvious policy response to natural uncertainty is that of irrigation as an answer to rainfall variability, which may not only alleviate the risk of drought but also smooth out within-season fluctuations of water supply. A number of qualitative and quantitative studies have shown that irrigation is an effective means to countervail the adverse effects of climate variability, such as loss of rainfall and high temperatures (e.g. Molua 2008, Hassan and Nhemachena 2008, Carsky et al. 1995). Kurukulasuriya and Mendelsohn (2006), for example, examine how climate affects the net revenues of dryland and irrigated land controlling for the endogeneity of irrigation. They find that precipitation has virtually no effect on the net revenues of irrigated farms, implying that irrigation serves as a buffer against rainfall variation. Similar findings are provided by Kurukulasuriya and Mendelsohn (2008). A trial experiment in the Maroua-Salak region by Carsky et al. (1995) demonstrated that the response of dry season sorghum to supplemental irrigation is substantial with up to 60 percent yield increases. They therefore suggest that research should focus on improvements in soil moisture availability. For the second scenario we therefore test the effects of a project on improved irrigation in sorghum production as a model case for other similar development projects. Based on Carsky et al. (1995) we assume a 55% increase in sorghum yields in bad years by improved soil moisture. Apart from the income-increasing effect such an improvement in sorghum cultivation would also most certainly result in lower correlation of sorghum yields with other crops.

Another proposition to address the problem of poverty and vulnerability is to provide additional income for the poor through diversification in fish production (CGIAR 2005). However, a major obstacle to risk-reduction via diversification is the almost perfect correlation of crops and fishing activities for our sample population. If the dependency of fishers on climatic conditions such as rainfall could be alleviated, income variation from fishing could be disconnected from the variation in agricultural income. This effect is assumed to be best achieved through aquaculture and bringing new small bodies of freshwater into fish production (CGIAR 2005). Similar to the effect of irrigation, which smoothes crop yields, fish production through aquaculture is assumed to significantly reduce the dependence on rainfall and reproduction rates of the fish stock in the Maga Lake, the Logone and its tributaries, and would hence particularly address the problem of high correlation of income. Since making assumptions concerning the income-increasing effect of an aquaculture project would be elusive, we simply estimate the risk-reducing effect of decreasing covariation between fish and crop production by setting the correlation factor to zero.

The results of scenario analysis are presented for both, the $LPM_{1,PL}$ and $LPM_{1,mean}$. The difference between the vulnerability indicator at $x=PL$ and $x=E[u]$ is that the former captures both, shifts in the mean of income as well as the variance, while the latter is showing the effect of changes in variance only, since shifts in the mean do not have an impact on negative deviations from $E[u]$. The results of the scenario analysis are presented in Table 5.

The simulated effects of different scenarios are overall comparable between the poor and the non-poor households. Increasing climate variability (extreme events scenario) has a risk increasing impact on all households, except for poor households at $x=PL$. We find that the expected shortfall from the poverty line is decreasing for this group. Hence, despite increasing variance and $LPM_{1,mean}$, weather shocks might have a slight positive effect in terms of poverty reduction (although statistically not significant). This is mainly due to the scenario specification, where we assume an increase of both, adverse and favorable climatic conditions. The small-scale irrigation scenario for sorghum production (sorghum increases) has a vulnerability-decreasing effect across the board, but naturally more so for sorghum farmers. Particularly the poor would benefit most from such development interventions (shortfall probability is decreasing by 15 and the expected shortfall by 26 percent compared to the original scenario). The aquaculture project scenario (assuming zero correlation between fishing and crop incomes) is also working in a favorable direction, i.e. the expected shortfall is decreasing for all groups, primarily for fishermen.

Table 5: Expected shortfall (LPM_1) for two targets: PL = poverty line (50% of average income) and E[u] = time-mean household portfolio income, by livelihood group and scenario

Poor					
		Sorghum growers	Millet growers	Rice growers	Fishermen
Original scenario	PL	53.42	54.29	78.21	71.01
	E[u]	16.38	12.90	12.18	16.01
Extreme events scenario	PL	52.57	55.41	77.94	69.20
	E[u]	21.54***	16.34***	14.21***	19.97**
Sorghum increases scenario	PL	39.39***	53.80	78.06	67.07
	E[u]	12.89***	12.77	12.15	14.75
Aquaculture project scenario	PL	53.20	54.05	77.83***	70.27
	E[u]	15.88	12.37*	11.50***	13.90**

Non-poor					
		Sorghum growers	Millet growers	Rice growers	Fishermen
Original scenario	PL	10.28	4.22	3.24	4.68
	E[u]	65.23	36.55	31.11	76.28
Extreme events scenario	PL	14.23***	5.98**	5.69***	7.37***
	E[u]	80.25***	42.40***	37.75***	92.84***
Sorghum increases scenario	PL	6.86***	4.22	3.01*	4.43**
	E[u]	57.19***	36.55	30.66**	74.95**
Aquaculture project scenario	PL	10.04*	3.57***	2.80***	3.40***
	E[u]	64.68**	33.52***	28.87***	67.44***

Poor and Non-poor					
		Sorghum growers	Millet growers	Rice growers	Fishermen
Original scenario	PL	14.54	22.76	40.73	11.31
	E[u]	60.40	27.79	21.64	70.25
Extreme events scenario	PL	18.02***	24.29**	41.81	13.55***
	E[u]	74.44***	32.75***	25.98***	85.56***
Sorghum increases scenario	PL	10.07***	22.58	40.54**	10.69
	E[u]	52.81***	27.74	21.41**	68.93***
Aquaculture project scenario	PL	14.30**	22.27***	40.31***	10.09***
	E[u]	59.85**	25.68***	20.18***	62.09***

Source: own data

Note: *, **, *** indicate significance levels of difference in mean to original scenario at 0.1, 0.5 and 0.01, respectively (paired T-test).

Figure 2 illustrates the impact of the assumed scenarios on LPM_1 for the total sample.

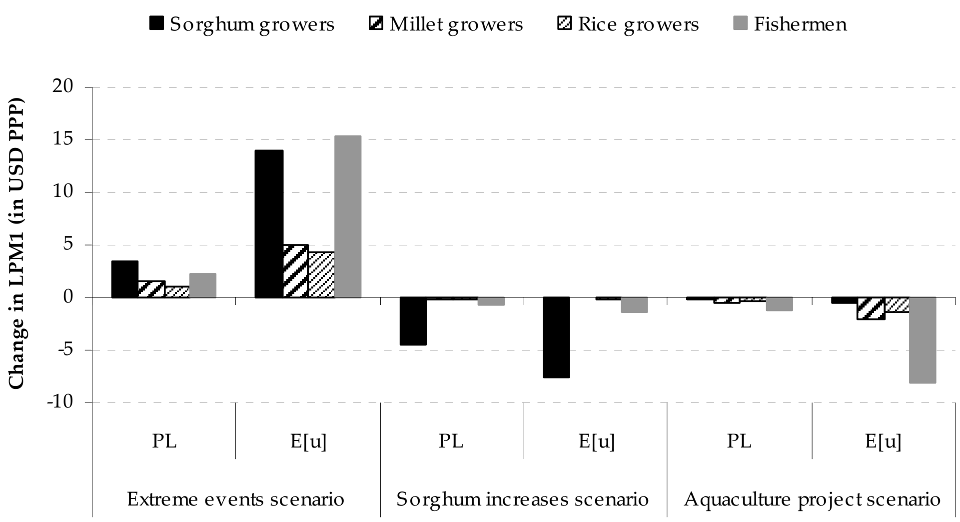

Figure 2: Changes of LPM1 in USD, by livelihood group and scenario

Source: own data

Thus, increasing climate variability would first and foremost affect sorghum growers and fishermen, and particularly increase transient poverty. This could be offset by irrigation for sorghum farmers and aquaculture projects for the fishermen.

Conclusions

In this paper we use the class of Lower Partial Moments (LPMs) for measuring vulnerability as downside risk of household income in rural Cameroon. This class of established and coherent risk measures is mainly used in the analysis of financial assets and has been shown to meet a number of desirable properties or axioms. Among others, the LPMs fulfill the focus axiom, and for order greater than zero they are in harmony with expected utility theory under the weak assumption of risk aversion. Through combining the vulnerability measure with a portfolio approach we are able to distinguish different livelihood systems for which the poverty and vulnerability measures are the explicit result of stochastic distributions of single activities in the households' portfolio and their covariance structure. Comparing LPMs of different order also allows to make conclusions concerning the risk of income loss (expected shortfall below the poverty line) as well as the distribution of vulnerability.

The results presented here basically show the structural probability to be poor and the risk of income losses, given the households production system and the variation in yield levels and prices in the past 10 years. As such, the vulnerability estimates reflect expected time-mean poverty. The results suggest that fishermen are less affected by adverse effects on income than other livelihood systems, while rice farmers are the poorest and most vulnerable. If we interpret the FGT measure as chronic poverty, it can be concluded that rice and millet farmers are suffering from chronic poverty, while transient poverty is more prevalent among the group of sorghum farmers and fishermen. This implication is further confirmed by assuming a moving target equal to the mean portfolio income for the calculation of LPMs. The results show that fishermen face a high risk of not maintaining the time-mean welfare level, despite low vulnerability to poverty (if poverty is defined at a fixed threshold, below which households are considered as poor). This trend is likely to become more intense, if climate variability will further increase, as suggested by climate change research. However, the results of the scenario analysis suggest that policy interventions aiming at a reduction of the covariation structure between income flows from different activities are quite promising.

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