Seasonal bias in household vulnerability to poverty stimates: insights from a natural experiment

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Abstract

Using data from 260 households from the Hadejia-Nguru wetlands, the paper shows that vulnerability to poverty estimates are biased if the data used is seasonal. The seasonal bias in the consumption expenditure is less pronounced than in its variance. The paper further shows that the relative sizes of the seasonal bias in expected consumption expenditure and its variance determines the final magnitude of the bias. However, the bias in the expected consumption expenditure is sufficiently corrected by including seasonal dummy variables. We therefore encourage researchers to consider seasonality when they are modelling consumption expenditure with the aim of estimating vulnerability.

1 Introduction

In one of the earliest and widely quoted studies on vulnerability to poverty[1], Pritchett et al. (2000) used two panel data sets from Indonesia and found that vulnerability to poverty was higher in one panel data set by 17 percent points than it was in another over the same period. They cited failure to take into account of seasonality, differences in the coverage of the panel data sets, and possibility for measurement error as possible explanations for the differences in the estimates. The assertion that seasonality may have played a role was not tested in study and has not been tested in recent vulnerability studies. Our study therefore explores this by assessing seasonal biases in vulnerability to poverty by using a data set that have controlled for coverage and probably measurement error. We argue that the vulnerability estimates that are derived from consumption expenditure data that is collected at different times of the year possess in them seasonal effects which may lead to upward or downward biases in the estimates. Whether the bias will be upward or downward depends on the relative magnitudes of seasonal bias in the expected consumption expenditure and its variance.

The study is relevant because most of the researchers that have estimated vulnerability to poverty have used survey data in which consumption expenditure has been used as a welfare indicator. However, expenditure surveys collects food expenditure data on shorter recall periods say seven days. This means that the food consumption expenditure will depend on the time of the year the household was interviewed and this will influence

[1] Among some authors Pritchett et al. (2000) has been cited by Chiwaula et al. (2011); Christeansen and Subbarao (2005); Ligon and Schechter (2003); and Chaudhuri et al., (2002)

the total household consumption expenditure since food accounts for the largest share of total household consumption expenditure in poor households. Vulnerability estimates from these data sets will therefore reflect the influence of seasonality. We therefore highlight the consequences of seasonality in using such data on vulnerability estimates. The study is based on a natural experiment that is designed from data a three survey panel data set collected from households from the Hadejia-Nguru Wetlands in Nigeria.

2 Analytical framework

We define vulnerability as the probability that a household will be poor at a point in time in the future (Chaudhuri et al., 2002; Suryahadi and Surmarto, 2003; Christiaensen and Subbarao, 2005). Denoting vulnerability level of household, *h* in season *m* of year *t*, as v_{hmt}, household vulnerability is formally defined as:

$$\begin{aligned} v_{hmt} &= \Pr(c_{hmt} \leq z) \\ &= \int_{-\infty}^{z} f(c_{hmt}) d(c_{hmt}) \end{aligned} \qquad 1$$

where c_{hmt} is the per capita consumption expenditure for household *h* in season *m* of year *t*; *z* is the poverty line; and *f(.)* is the probability distribution function of consumption in season *m* of year *t*. Due to data limitations Chaudhuri et al. (2002) and Chaudhuri (2003) directly assumed that household consumption is log-normally distributed, and they used household characteristics to predict the mean and variance of future consumption. We follow these authors and empirically estimate vulnerability as follows:

$$v_{hmt} = \Pr(\ln c_{hmt} < \ln z | X_{hmt}) = \Phi\left(\frac{\ln z - \ln c_{hmt}}{\sqrt{\text{var}(\ln c_{hmt})}}\right) \quad 2$$

Where X_{hmt} is the vector of household characteristics; $\Phi(.)$ denotes the cumulative density of the standard normal; and $\text{var}(\ln c_{hmt})$ is the household specific variance of consumption expenditure in season *m* of year *t*.

The main objective in this section is to show that equation 2 results in different annual vulnerability estimates for the same households if the data was collected in different seasons. The different results will be obtained because of the seasonality in expected consumption and its variance.

2.1 Seasonality in expected consumption

We use the buffer-stock model of household consumption (Deaton, 1991; Deaton and Paxson, 1994; Chaudhuri and Paxson, 2002) to derive the seasonal consumption expenditure functions. This model assumes that households are not permitted to borrow, an assumption that is plausible for the conditions in many rural agrarian communities. Consumers in this model are also assumed to be impatient such that they prefer consumption now to consumption later, and they are not persuaded by the rewards of waiting. This means that the rate of time preference for the consumers (δ) exceeds the rate of return, *r*. Impatience prevents long-term asset accumulation, but caution coupled with borrowing constraints provides incentives to hold a buffer of assets in most periods. In this case, consumers save only to buffer their consumption from short term income fluctuations.

Assuming that there are two seasons 1 and 2 in a given year *t*, and that infinitely living consumers choose seasonal consumption levels to maximise a discounted additively separable utility function:

$$u_{1t} = \sum_{j=0}^{\infty} E_{jt} \left[u(c_{1,t+j})\beta^{2j} + u(c_{2,t+j})\beta^{2j+1} \right] \qquad 3$$

where $\beta = 1 + \delta$ and δ is the time preference for the consumers, c_{mt} is the consumption in season *m* of year *t*, and $u(c_{mt})$ is the instantaneous (sub)utility function, assumed to be increasing, strictly concave, and differentiable.

Let us define the cash-on-hand for a household in a given season *m* of year *t*, a_{mt} as being equal to the sum of assets held over from the previous season $(a_{m-1,t} - p_{m-1,t}c_{m-1,t})$, plus income earned in the present season, y_{mt}:

$$a_{mt} = R(a_{m-1,t} - p_{m-1,t}c_{m-1,t}) + y_{mt} \qquad 4$$

Where $R = 1 + r$ and *r* is the interest rate, and p_{mt} is the price of consumption in season *m* of year *t*. Specifically for seasons 1 and 2 of year *t*, the asset evolution constraint is given by:

$$\begin{aligned} a_{2t} &= R(a_{1t} - p_1 c_{1t}) + y_{2t} \\ a_{1t} &= R(a_{2,t-1} - p_2 c_{2,t-1}) + y_{1t} \end{aligned} \qquad 5$$

In the absence of major negative and positive shocks, consumption and production (income) in corresponding seasons of different years are assumed to be equal. If this assumption holds, then $a_{2,t-1} = a_{2t}$ and $c_{2,t-1} = c_{2t}$. Utility maximisation of the intertemporal utility function 3 leads to the following Euler equation:

$$u'(c_{1t}) = \beta R u'(c_{2t}) \qquad 6$$

This is a common result in inter-temporal consumption optimisation (for example see Deaton, 1991; Chaudhuri and Paxson, 2002). Assuming that the utility function takes the constant relative risk aversion (CRRA) form, such that $u(c_{1t}) = \frac{c_{1t}^{1-\theta}}{1-\theta}$, where θ is the risk aversion parameter then, $u'(c_{1t}) = c^{-\theta}$. Substituting this marginal utility into Euler equation 6, an equation that relates consumption in the two seasons is obtained:

$$c_{1t} = (\beta R)^{-\frac{1}{\theta}} c_{2t} \qquad 7$$

Substituting equation 7 into the budget constraint (equation 5) and rearranging the equations results in seasonal specific consumption equations c_{1t}^* and c_{2t}^* which when multiplied with the prices of consumption results in season specific consumption expenditures presented below:

$$E_{2t}^* = p_2 c_{2t}^* = \frac{\lambda p_{2t}}{R p_{1t}} \left[R a_{1t} - a_{2t} + y_{2t} \right]$$

$$E_{1t}^* = p_1 c_{1t}^* = \frac{\lambda p_{1t}}{R p_{2t}} \left[R a_{2t} - a_{1t} + y_{1t} \right] \qquad 8$$

Where $\lambda = (\beta R)^{\frac{1}{\theta}}$. The results in equation 8 show that seasonal consumption expenditure is positively related to seasonal flow in income and the net of the assets held between the two seasons. This implies higher consumption during the harvesting season and lower consumption during the lean season. The net of asset holdings between the two seasons implies the use of savings to smooth consumption. Consumers are saving to maintain a certain desired consumption level which is consistent with the consumer's permanent income.

The effect of price in a given season on consumption expenditure in that season is direct where an increase in price increases expenditures and vice versa. On the other hand, price in one season has inverse effects on consumption expenditure in the other season. Increase in price of the consumption in one season reduces consumption expenditure in the coming season. In principle households will not consume everything if they expect the price to increase in the coming season and they may consume everything if the price of consumption is expected to go down in the coming season.

2.2 Seasonality in the variance of expected consumption

From the theoretical model above and from earlier related work (Hall and Mishkin, 1982; Moffitt and Gottschalk, 2002; Abe, 2008) it can be stated that observed seasonal consumption expenditure for a given household, *h* in season *m* of year *t*, E_{hmt} is composed of three components:

$$E_{hmt} = E^{*}_{hm-1t} + \upsilon_{hmt} + \varepsilon_{hmt} \qquad 9$$

where E^{*}_{hm-1t} is the desired expenditure in season *m-1* of year *t*, υ_{hmt} is an independently and identically distributed temporary (seasonal) shock in expenditure, and ε_{hmt} is an independently and identically distributed permanent (long term) shock in expenditure. This formulation assumes that consumption expenditure is measured with no or minimum error which is a strong assumption but cannot be relaxed because the data we have cannot allow us to account for measurement error. The desired consumption expenditure is the same as the deterministic component of consumption expenditure and this depends on the household endowments and preferences. The desired expenditure in the previous season can therefore be thought of as the permanent component of consumption which is time varying but is expected to persist.

If it is assumed that the desired consumption expenditure in the previous season, the permanent shock on consumption expenditure, and the temporary (seasonal) shock on consumption expenditure are not correlated, that is, $\mathrm{cov}(E^{*}_{hm-1,t}, \varepsilon_{hmt}) = 0$, $\mathrm{cov}(E^{*}_{hm-1,t}, \upsilon_{hmt}) = 0$, and $\mathrm{cov}(\upsilon_{hmt}, \varepsilon_{hmt}) = 0$, the variance of observed seasonal consumption expenditure in season *m* of year *t* can be given as:

$$\mathrm{var}(E_{hmt}) = \mathrm{var}(E^{*}_{hm-1,t}) + \mathrm{var}(\upsilon_{hmt}) + \mathrm{var}(\varepsilon_{hmt}) \qquad 10$$

Equation 10 shows that, the variance of consumption expenditure of a given household in a given season is the sum of the variances of the expected consumption in the previous period, the long term shock, and the short term shock. This means that two panel data sets that have the same current season, *m* but different preceding seasons, *m-1* will produce different estimates of the variance of consumption expenditure. Specifically, if the preceding season is characterised by the high consumption expenditure and high variance (e.g. harvesting season) higher estimates of variance will be obtained in the current season and vice versa.

3 Data and empirical application

The study uses a balanced panel data set of 260 households that is composed of three survey rounds. The three surveys were conducted after a comprehensive baseline survey which was conducted in April 2007. The surveys were conducted in the Hadejia-Nguru Wetlands in Nigeria in August 2007, November 2007 and March 2008. The survey that was conducted in August collected consumption data for the period between April and August and this is termed dry season. This is about 6 months after households harvested their produce from the main cropping season. The November survey collected consumption data for the period between August and November. This is termed the farming season because it is during this time when the area receives most rainfall and most of the farming activities take place during this period. This period also coincides with an increase in fishing opportunities due to the increase in water levels. Finally, the March survey is termed the harvesting period because most households in this period are harvesting their farm produce. The recall period is between November and March.

From the data collected from the three surveys, a natural experiment was designed to test the propositions made by this study. In designing these experiments, it was assumed that there are two panel data sets that have a common second round survey (March 2008 survey) but they differed in the preceding surveys. In the first data set, the August 2007 survey is assumed to precede the March 2008 survey while the second data set, the

November 2007 survey is preceding the March 2008 survey. Table 1 below gives the outline of natural experimental designs together with the complete panel which acted as the control panel data set.

Table 1: Design of natural experiment to assess effect of timing and frequency of surveys on vulnerability estimates in the Hadejia-Nguru Wetlands

Survey date	April 2007	August 2007	November 2007	March 2008
Season covered	Whole year	Dry season	Farming season	Harvesting season
Recall period	April 2006 to April 2007	April 2007 to August 2007	August 2007 to November 2007	November 2007 to March 2008
Panel 1				
Panel 2				
Control				

Note: Shaded areas symbolise data from that survey is included in that panel data set

Source: Own illustration

Empirical application aims at showing season bias in expected consumption expenditure, its variances, and vulnerability to poverty if the preceding seasons are different. Following Just and Pope (1979), Chaudhuri (2003), Christiaensen and Subbarao (2005), we used a three step feasible generalized least square technique (3-FGLS) to estimate consumption expenditure and its variance. The formulation allows the household endowments and characteristics to affect both the expected mean consumption and variance of expected consumption. Allowing the variance to depend on household endowments makes the specification heteroskedastic which is a less restrictive specification. The models were estimated using the random effect estimator following the results of the Hausman test.

4 Results and Discussion

4.1 Descriptive statistics

The descriptive statistics of the variables that have been used in this paper are presented in Table 2 below:

Table 2: Descriptive statistics for variables used in assessing seasonal vulnerability in the Hadejia-Nguru wetlands, Nigeria

	Dry season		Farming season		Harvesting season	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Real consumption expenditure (Naira)	91.08	83.68	93.83	101.18	113.82	132.42
Age head (years)	42.56	14.46	42.56	14.46	42.56	14.46
Education head (1/0)	0.27	0.44	0.27	0.44	0.27	0.44
HH size	7.30	3.33	7.97	4.07	8.22	4.13
Dependency ratio	0.54	0.18	0.53	0.20	0.51	0.21
Associations	0.62	0.74	0.62	0.74	0.62	0.74
Land holding (ha)	1.06	1.16	1.06	1.16	1.06	1.16
Farming assets (Naira)	2661.61	3550.52	2661.61	3550.52	2661.61	3550.52
Fishing assets (Naira)	475.16	1014.61	475.16	1014.61	475.16	1014.61
Livestock value (Naira)	11593.45	19836.45	11593.45	19836.45	11593.45	19836.45
Drought (1/0)	0.08	0.27	0.08	0.27	0.08	0.27
Field pests (1/0)	0.30	0.46	0.30	0.46	0.30	0.46
Health (1/0)	0.50	0.50	0.50	0.50	0.50	0.50
Conflict (1/0)	0.23	0.42	0.23	0.42	0.23	0.42
Flood (1/0)	0.06	0.24	0.06	0.24	0.06	0.24
Hadejia (1/0)	0.30	0.46	0.30	0.46	0.30	0.46
N	260		260		260	

Note: All quantities and amounts are measured in per capita

Source: Own computations based on own data

The real consumption expenditure is found to vary seasonally. The mean consumption expenditure per person per day is lowest during the dry season and highest during the harvesting season. Some of the variables such as assets were expected to change marginally between seasons. That is why they were assumed to be constant over the year.

4.2 Seasonal bias in vulnerability

Following the estimation procedures discussed above we estimated household expected consumption expenditure and its variance under three treatments in March 2008. For each of the panel data sets, two regression models were estimated. One model included a seasonal dummy variable as one of regressors to control seasonality while the other did not[2]. The results of the estimated consumption expenditure are presented in Table 3 below.

Table 3: Estimated seasonal bias in expected consumption expenditure

Treatment	Description	Mean	Std. Dev.
Control	All survey rounds	4.331	0.612
Panel 1 with season dummy	Excluding dry season	4.333	0.624
Panel 1 without season dummy	Excluding dry season	4.208[a]	0.614
Panel 2 with season dummy	Excluding farming season	4.333	0.605
Panel 2 without season dummy	Excluding farming season	4.231[a]	0.599

Note: [a]denotes that value is significantly different from the control case.

Source: Own estimations based on own data

[2] Regression results that were used to estimate expected consumption expenditure and its variance are not presented to save space but can be made available upon request.

The results show that the estimated consumption expenditure for a given season is almost the same even if previous seasons are different if the regression models control for seasonality. If the regression models does not control for seasonality, the consumption expenditure is underestimated. This means that the inclusion of the seasonal dummy variables in the estimations assist in correcting the bias in the estimated values of mean consumption expenditure. Results of the estimated variance are presented in Table 4 below:

Table 4: Estimated seasonal bias in variance of expected expenditure

Treatment	Description	Mean	Std. Dev.
Control	All survey rounds	0.056	0.024
Panel 1 with season dummy	Excluding dry season	0.042 [a,3]	0.017
Panel 1 without season dummy	Excluding dry season	0.057 [4]	0.019
Panel 2 with season dummy	Excluding farming season	0.065 [a,1]	0.020
Panel 2 without season dummy	Excluding farming season	0.078 [a,2]	0.024

Note:

[a] denotes that significantly different from the control case, [1]denotes that the estimates are significantly different from panel data set 1 with dummy variables during estimation, [2]denotes that estimates are significantly different from panel data set 1 without dummy variables during estimation, [3]denotes that the estimates are significantly different from panel data set 2 with dummy variables during estimation, [4]denotes that estimates are significantly different from panel data set 2 without dummy variables during estimation all

The results show that the variance of consumption expenditure in March 2008is lower when the dry season is excluded than when the farming season is excluded. When the dry season is excluded, the farming season is the preceding season in the panel data set and vice versa. The descriptive statistics in Table 2 shows that expenditure and its standard deviation in the faming season are larger than they are during the dry season. This means that the panel data set that has the farming season as its previous season will have a larger variance because the variance of consumption in the previous period, $\mathrm{var}(E^{*}_{hm-1,t})$ for that data set is larger. These results are therefore consistent with the results of the theoretical model (equation 8) which means that the variance depends on the variance of the preceding period.

Using the estimated consumption expenditure and its variance, vulnerability to poverty estimates were derived using equation 2 and these results are presented in Table 5 below.

Table 5: Estimated seasonal bias in vulnerability

Treatment	Description	Mean	Std. Dev.
Control	All survey rounds	57.9	41.7
Panel 1 with season dummy	Excluding dry season	57.8	43.2
Panel 1 without season dummy	Excluding dry season	64.2[a]	40.4
Panel 2 with season dummy	Excluding farming season	57.8	41.0
Panel 2 without season dummy	Excluding farming season	63.4	38.8

Note:

[a]denotes that significantly different from the control case.

The results show that vulnerability estimates are almost the same for panel data set 1 and panel data set 2. When season dummy variables are used these estimates are equal to the estimates that are obtained from the control treatment. When seasonal dummy variables are not used, vulnerability estimates from both treatments are greater than the estimates from the control treatment. This is so because exclusion of the seasonal dummy variables results in the underestimation of consumption expenditure, although this results in overestimation of variance. This means that the final effect of seasonality on vulnerability estimates will depend on the relative sizes of seasonal biases in expected expenditure and its variance.

5 Concluding remarks

In this paper, we argue that vulnerability to poverty estimates are likely to be biased if seasonality in the data is not controlled for. The findings of the study has confirmed this and they have further shown that the relative sizes of the seasonal bias in expected consumption expenditure and its variance will determine the final size of the bias. The seasonal bias in the consumption expenditure is less pronounced than in its variance. Further to that, the findings show that the bias in the expected consumption expenditure is sufficiently corrected by including seasonal dummy variables. We therefore encourage researchers to consider seasonality when they are modelling consumption expenditure with the aim of estimating vulnerability. When using annual consumption surveys where households have been interviewed in different seasons of the year, it is advisable for researchers to control for seasonality but considering the season of the survey. When planning consumption expenditure surveys that will be used to estimate vulnerability, researchers are encouraged to collect data in the same seasons of different years if the estimates are to be interpreted as annual otherwise the estimates can be interpreted as seasonal.

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References

Abe, N., 2008. Volatility in panel data of household expenditure. Discussion paper No. 237. Hitotsubashi University Research Unit for Statistical Analysis in Social Sciences. Tokyo, Japan.

Chaudhuri, S. (2003). Assessing vulnerability to poverty: concepts, empirical methods and illustrative examples. Unpublished manuscript.

Chaudhuri, S., J. Jalan and A. Suryahadi (2002). Assessing household vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia. Discussion Paper No. 0102-52. Columbia University, 36 pp.

Chaudhuri, S. and C. Paxson, 2002. Smoothing consumption under income seasonality: buffer stocks vs. credit markets. Columbia University Discussion paper Number: 0102-54

Chiwaula, L.S, R. Witt and H. Waibel., 2011 An Asset-Based Approach to Vulnerability: The Case of Small-Scale Fishing Areas in Cameroon and Nigeria. *Journal of Development Studies.* 47(2): 338 - 353

Christiaensen, L. J. and K. Subbarao, 2005. Towards an understanding of household vulnerability in rural Kenya. *Journal of African Economies*, 14(4): 520 – 558.

Deaton, A., and C. Paxson, 1994. Intertemporal choice and inequality. *The Journal of Political Economy*, 102(3): 437-467

Deaton, A., 1991. Saving and liquidity constraints. *Econometrica*, 59(5): 1221- 1248

Günther, I. and J. Maier, 2008. Poverty vulnerability and loss aversion. UNU-WIDER Conference on Frontiers of Poverty Analysis. Helnsinki.

Hall, R.E and F.S Mishkin, 1982. The sensitivity of consumption to transitory income: Estimates from panel data on households. *Econometrica*, 50(2): 461 – 481

Just, R.E and R.D. Pope, 1979. Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, 61(2): 276-284.

Ligon, E. and Schechter, L., 2003. Measuring Vulnerability. *The Economic Journal*, 113, pp. C95-C102.

Makoka, D. (2008). Risk, risk management and vulnerability to poverty in rural Malawi. A published PhD Thesis. Cuvillier Verlag, Goettingen, Germany.

Moffitt R.A. and P. Gottschalk, 2002. Trends in the variance of Permanent and Transitory Earnings in the US and their relation to earnings mobility. *The Economic Journal*, 112(March); C68-C73

Prichett, L., A. Suryahadi and S. Sumarto, 2000. Quantifying vulnerability to poverty. A proposed measure, with application to Indonesia. SMERU Working paper

Suryahadi, A. and S. Sumarto (2003). Poverty and vulnerability in Indonesia before and after the economic crisis. *Asian Economic Journal*, 17(1), pp. 45-64.