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Household Poverty Dynamics in Malawi: A Bivariate Probit Analysis

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A Bivariate Probit Analysis of Household Poverty Dynamics in Malawi

Abstract

This paper's goal is to identify the sources of expenditure and poverty dynamics among Malawian households between 1998 and 2002 and to model poverty transitions in Malawi using a bivariate probit model with endogenous selection to address the ''initial conditions' problem. The exogeneity of the initial state is strongly rejected and could result in considerable overstatement of the effects of the explanatory factors. The results of the bivariate probit model do indicate that education of the household head, per capita acreage cultivated and changes in household size are significantly related to the probability of being poor in 2002 irrespective of the poverty status in 1998. For those households who were poor in 1998, the probability of being poor in 2002 was significantly influenced by household size, value of livestock owned and mean time to services, while residence in the Northern region was a significant variable in determining the probability of being poor in 2002 for households that were not poor in 1998.

Key terms: *Poverty transitions, characteristics of the poor, poverty dynamics, determinants of poverty, Malawi*

INTRODUCTION

This paper investigates the dynamics of poverty determinants in Malawi between 1998 and 2002. Understanding the nature and dynamics of these determinants may be critical in the identification of factors driving the changes in consumption behaviours. This is of interest for researchers because it makes possible to find out how changes in welfare indicator (for this paper the welfare measure is the per capita consumption expenditure) make households move within the expenditure distribution over time. In Africa, very few empirical studies exist on the dynamics of poverty based on individual households, due to a lack of panel data. In a recent review regarding research on the dynamics of poverty, Baluch and Hoddinot (2000) report that only four African countries (South Africa, Cote d'Ivoire, Ethiopia and Zimbabwe) have household-level panel data.

A number of different approaches have been used to understand the factors associated with poverty dynamics and poverty transitions. Many studies though complement descriptive analysis with an explicitly econometric approach. In this line McCulloch and Baulch (1999) distinguished the chronically and transitorily poor households for Pakistan based on the components method. In this approach the characteristics associated with being chronically, transitorily or never poor using both an ordered logit model and a multinomial logit model.

Where the time dimension of panel data sets are relatively long, it becomes possible instead to model the duration of poverty spells, an approach initially adopted by Bane and Elwood (1986) for the United States. Along similar lines, Baulch and McCulloch (1998) model the probability of entering and exiting from poverty in Pakistan using a proportional hazards model and allowing for censoring. This is justified on the basis that the factors that are correlates of poverty transitions are not often the same as those that are correlates of the level of living standards of poverty itself.

It is also possible to use a spells approach even when the time dimension is shorter. Bhidea and Mehta (2003) based on a two wave panel data for India covering the period 1970/71 to 1980/81. Carter and May (1999) with a two wave panel for Kwa-zulu Natal, South Africa also modelled movements into and out of poverty while Okrasa (1999) estimates logit equations for both the likelihood that a household is vulnerable and that it is chronically poor in Poland. However**,** Jalan and Ravallion (2000) model the factors associated with each spell using a censored quantile regression model. Other studies have modelled income dynamics of households over time these include Dercon (2003) and Fields et al (2001). In practice some of these different approaches complement each other and in this paper I apply the biprobit model to study the determinants of poverty dynamics in Malawi.

To my knowledge, lack of panel data has precluded investigation of poverty dynamics in Malawi. The central questions that this paper addresses are: What factors account for the pattern of long-term poverty? How important are household characteristics in determining the risk of falling into or the chance of moving out of poverty?

MATERIALS AND METHODS

Data: Data used in this paper comes from two sources. Panel data is generated from two household surveys in 1998 and 2002. The first panel comes from household survey done in 1998 by the Malawi National Statistical Office (NSO) in the Integrated Household Survey (IHS). The second panel comes from the Complementary Panel Study (CPS), done in 2002 by Centre for Social Research (CSR) of the University of Malawi. The households in the CPS are a sub-sample of the households drawn in the IHS. Both surveys collected data on the demographic characteristics of households, education, health status, own production, income and expenditure and employment. I obtained a usable sample of a matched panel of 291 rural households from 13 districts.

Model: Many recent studies have used the multinomial logit model for analysing the factors affecting the probability that a household is in chronic poverty (as opposed to transient poverty or being non-poor). One of the main advantages of such an approach is ease of specification (Glewwe and Hall 1995; Grootaert and Kanbur 1995). The ease of usage partly explains why the model has been chosen so frequently. However the main drawback is that it imposes the property of 'independence of irrelevant alternatives' (This property is a consequence of the implied assumption of no correlation between the error terms) and also the fact that it is not really a model of transitions. One solution is to consider the factors associated with whether a household is poor or not to start with separately from the factors associated with changes (or not) in the household's poverty status between 1998 and 2002 by means of three separate logit models, however, conditioning on the initial poverty state produces biased estimates if the initial state is not exogenous. Non-exogenous initial state can cause sample selection bias, implying that true representation and inferences may be distorted with standard modelling techniques (Heckman, 1981). A solution to the problem is to use a bivariate probit model.

The interest lies in the probability that a poor household in year 1 is also in poverty in year 2. Assume that the following process generates the per capita household expenditure.

$$f_1(Y_{i1}) = \chi_{i1}\beta_1 + \varepsilon_{i1} \tag{1}$$

where Y_{i1} is per capita household expenditure for household i in year 1, χ_{i1} is a vector of expenditure determining characteristics, $\varepsilon_{i1} \sim N(0,1)$, and f_1 is an unspecified suitable monotonic transformation, ensuring the standard normal distribution of ε_{i1}. The probability that expenditure falls below the poverty threshold is given by:

$$prob(P_{i1} = 1) = prob(Y_{i1} \leq Lp1) = prob(f_1(Y_{i1}) \leq f_1(Lp1)) = \Phi(f_1(Y_{i1}) - \chi_{i1}\beta_1) = \Phi(\chi_{i1}\beta_1) \tag{2}$$

where P_{i1} is an indicator variable equal to 1 if per capita household expenditure falls below the poverty threshold $Lp1$ and 0 otherwise. Φ is the standard normal cumulative distribution function, giving a probit model for the probability of being poor.

If the per capita household expenditure in year 2 depends on the poverty status in year 1, for the poor household in year 2, the per capita household expenditure is generated by the process

$$f_2(Y_{i2}) = \omega_{i2}\beta_1 + \varepsilon_{i2} \tag{3}$$

ω_i now represents transition determinants that are variables explaining expenditure status in year 2, given the poverty status in year 1. The monotonic transformation f_2 ensures the standard normal distribution of ε_{i2}. Although this relationship is defined for households with $Y_{i2}=1$, it is assumed to apply even to households who were not poor in year 1. It is further assumed that the distribution of the error term (ε_{i1}, ε_{i2}) is bivariate standard normal with correlation coefficient ρ, -1< ρ <1. The probability of household *i* being poor in year 2 given that it is poor in year 1, is:

$$prob(P_{i1} = 1, P_{i2} = 1) = prob(Y_{i1} \leq Lp1, Y_{i2} \leq Lp_2) = \Phi_2(\chi_{i1}\beta_1, \omega i2\beta_2; \rho) \tag{4}$$

Where Φ_2 is the cumulative distribution function for the bivariate standard normal. Consistent with the definition of conditional probability, then the probability of being poor in year 2 given being poor in year 1 is given by;

$$prob(P_{i2} = 1 | P_{i1} = 1) = \frac{prob(P_{i1} = 1, P_{i2} = 1)}{prob(P_{i1} = 1)} = \frac{\Phi_2(\chi_{i1}\beta_1, \omega_{i2}\beta_2; \rho)}{\Phi_2(\chi_{i1}\beta_1)} \tag{5}$$

In a special case where ρ= 0, the zero correlation implies that lack of dependence between poverty status in year 1 and poverty status in year 2 and the probability of poverty in year 2 simplifies to a standard univariate probit model

$$prob(P_{i2} = 1 \mid P_{i1} = 1) = \frac{prob(P_{i1} = 1, P_{i2} = 1)}{prob(P_{i1} = 1)} = \Phi(\omega_{i2}\beta_2) \quad (6)$$

The probability of being non poor in year 2 and poor in year 1, is defined analogously to equation 7.

$$prob(P_{i1} = 1, P_{i2} = 0) = \Phi_2(\chi_{i1}\beta_1, -\omega_{i2}\beta_2; -\rho) \quad (7)$$

Since year 2 information is only used for those poor in year 1, the model is a bivariate probit with endogenous selection. This "double probit" model implies that household *i*'s contribution to the log-likelihood function is given by

$$LnLi = P_{i1}P_{i2}\ln\Phi_2(\chi_{i1}\beta_1, \omega_{i2}\beta_2; \rho) + P_{i1}(1 - P_{i1})\ln\Phi_2(\chi_{i1}\beta_1, -\omega_{i2}\beta_2; -\rho) + \ln\Phi_2(-\omega_{i2}\beta_2) \quad (8)$$

RESULTS AND DISCUSSION

The explanatory variables used in the bivariate probit model are presented in Table 1.

Table 1: Description of variables used in the bivariate probit model

	Type	Description
HHSZ	Continuous	Household size
MARRIED	Binary	Head of household married
PI00_09	Continuous	Number in the household below age 10
PI60_99	Continuous	Number in the household above age 60
AGE	Continuous	Household head: Age in years
AGESQ	Continuous	Household head: Age squared
SEXH	Binary	1 if male headed household
EDUCH1	Binary	Omitted category for head without formal education
EDUCH2	Binary	Household head attended primary school
EDUCH3	Binary	Household head attended secondary school
LNLVST	Continuous	Natural log of per capita value of livestock owned
PCLAND	Continuous	Per capita acreage cultivated
SALARY	Continuous	Household members with salaried employment
TIMEACC	Continuous	Mean time (hr) to services
REGION1	Binary	Omitted category for residing in the southern region
REGION2	Binary	1 if household resides in the central region
REGION3	Binary	1 if household resides in the northern region
CHHSZ	Continuous	Change in household size
CPI00_09	Continuous	Change in number of members below the age of 10
CPI60_99	Continuous	Change in number of members above the age of 60
CSALARY	Continuous	Change in number of members with salaried employment

The marginal effects of the bivariate probit model are presented in Table 2 and from the table the correlation coefficient between the errors of the two equations is statistically significant (the Likelihood Ratio Test for Ho: ρ=0 against H1: ρ≠0 gave a p-value of 0.22) thus rejecting the hypothesis that the two dependent variables are not jointly determined.

Table 2: Marginal Effects for the Bivariate Probit Model

(1)	(2) Probability of being poor in 2002 conditional upon being poor in 1998	(3) Probability of being poor in 2002 conditional upon being non poor in 1998
Household Composition		
HHSZ	0.050***	0.013
	[0.019]	[0.016]
MARRIED	-0.080	0.066
	[0.114]	[0.073]
PI00_09	0.042	0.002
	[0.028]	[0.026]
PI60_99	-0.022	0.005
	[0.063]	[0.072]
AGE	0.006	-0.006
	[0.009]	[0.088]
AGESQ	-0.000	0.000
	[0.000]	[0.000]
SEXH	-0.055	-0.019
	[0.095]	[0.086]
Education: reference category is no education		
EDUCH2	-0.111**	0.008
	[0.055]	[0.049]
EDUCH3	-0.325***	-0.127**
	[0.038]	[0.058]
Household Assets		
LNLVST	-0.025**	0.007
	[0.012]	[0.011]
PCLAND	-0.132**	0.121**
	[0.066]	[0.059]
Employment		
SALARY	-0.079	-0.020
	[0.059]	[0.047]
Access to services		
TIMEACC	0.093**	-0.032
	[0.038]	[0.033]
Regional dummies: reference category is Southern Region		
REGION2	-0.015	0.004
	[0.061]	[0.055]
REGION3	-0.106	-0.146***
	[0.067]	[0.045]
Change variables		
CHHSZ	0.045***	0.047***
	[0.012]	[0.013]

CPI00_09	0.020	0.021
	[0.017]	[0.017]
CPI60_99	-0.000	-0.000
	[0.010]	[0.011]
CSALARY	-0.048	-0.050
	[0.044]	[0.046]
Observations	291	291
Log Likelihood	-326.528	-326.528
Wald Chi2 (34)	118.19	118.19
Prob> Chi2	0.000	
Rho = 0.244		
Wald Test of rho=0: Chi2(1)= 5.254	Prob>Chi2 = 0.022	

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

From Table 2, the marginal effects of each variable on the joint probabilities of being poor in 1998 and poor in 2002 (column 2) and not being poor in 1998 and being poor in 2002 (column 3) are presented.

The probability of being poor in 2002 is reduced for those households whose head had attended secondary school. For households that were poor in 1998, the probability of being poor in 2002 reduces by 32.5 percentage points while for those households who were not poor in 1998 the probability of being poor in 2002 is reduced by 12.7 percentage points.

Another variable that had significance in both joint probabilities was per capita acreage cultivated; however, it had different impact in the two joint probabilities. For households who were poor in 1998 a unit increase in the per capita acreage cultivated reduced the probability of being poor in 2002 by 13 percentage points but increased the probability of being poor in 2002 by about 12 percentage points for households who were not poor in 2002.

A unit change in household size increased the probability of being poor in 2002, irrespective of the poverty status in 1998 by 5 percentage points.

Household size, primary school attendance of household head, value of livestock owned by the household and average time to access services were significant for the probability of being poor in 2002 for households that were poor in 1998 but not for households that were not poor in 1998. Household size and average time to access services increased the probability of a household being poor in 2002 by 5 and 9 percentage points respectively.

The probability of being poor in 2002 for households whose head had attended primary school reduced by 11 percent compared to those whose head had no education. The value of livestock owned was also negatively related to the probability of being poor in 2002; a unit increase in the value of per capita value of livestock owned reduced the probability of being poor in 2002 by about 3 percent.

Households residing in the Northern Region were 15 percent less likely to be poor in 2002 compared to households residing in the Southern region.

CONCLUSION

This dependence of the probability of being poor on past poverty experience may result either from heterogeneity among households or from the impact of the experience of poverty itself. It is important to address the initial conditions problem when modelling transition probabilities. The empirical evidence in this paper indicates that exogenous selection into the initial poverty ($\rho = 0$) is strongly rejected and that ignoring the endogenous selection of conditioning on the initial poverty distorts the estimated coefficients.

For those households who were poor in 1998, the probability of being poor in 2002 was significantly influenced by household size, value of livestock owned and mean time to services, while residence in the Northern region was a significant variable in determining the probability of being poor in 2002 for households that were not poor in 1998. There is evidence of considerable *ceteris paribus* dependence of the probability of being poor on whether or not a household was poor in the previous year. Finally, sustainable economic growth is the best solution for Malawi to reduce poverty overtime. A report by the Economic Commission for Africa (ECA, 2000) indicated that a growth rate of at least 6 per cent is required to make significant reduction in poverty.

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