Proxy Means Tests for Targeting the Poorest Households

Applications to Uganda

**Nazaire Houssou*, Manfred Zeller*, Gabriela Alcaraz V.*,
Stefan Schwarze**, Julia Johannsen****

*** Institute of Agricultural Economics and Social Sciences in the Tropics and Subtropics,
University of Hohenheim, 70599 Stuttgart, Germany**

**** Institute of Agricultural Economics and Rural Development,
University of Goettingen, 37073 Goettingen, Germany**

Paper prepared for presentation at the 106th seminar of the EAAE

Pro-poor development in low income countries:

Food, agriculture, trade, and environment

25-27 October 2007 – Montpellier, France

Abstract

The motivation for this research stems from increasing interest showed for the issue of targeting. The paper explores the use of proxy means tests to identify the poorest households in Uganda. The set of indicators used in our model includes variables usually available in Living Standard Measurement Surveys (LSMS). Previous researches seeking to develop proxy means tests for poverty most often use Ordinary Least Squares (OLS) as regression method. In addition to the OLS, the paper explores the use of Linear Probability Model, Probit, and Quantile regressions for correctly predicting the household poverty status.

A further innovation of this research compared to the existing literature is the use of out-of sample validation tests to assess the predictive power and hence the robustness of the identified set of regressors. Moreover, the confidence intervals are approximated out-of sample using the bootstrap algorithm and the percentile method.

The main conclusion that emerges from this research is that measures of absolute poverty estimated with Quantile regression can yield fairly accurate in-sample predictions of absolute poverty in a nationally representative sample. On the other hand, the OLS and Probit perform better out-of sample. Besides it complexity, the Quantile regression is less robust. The Probit may be the best alternative for optimizing both accuracy and robustness of a poverty assessment tool.

The best regressor sets and their derived weights can be used in a range of applications, including the identification of the poorest households in the country, the assessment of poverty outreach of Microfinance Institutions (MFIs), the eligibility to social transfer programs, and the measurement of poverty and welfare impacts of agricultural development projects. To confirm or reject the conclusions regarding the suitability of different regression methods, future research is needed to apply the regression and validation methods developed in this paper by using data sets from other countries.

Keywords – Uganda, Poverty assessment, Targeting, Proxy means tests, Out-of-sample test, Bootstrap

1. Introduction

Over the past decades, there was a surge in attention towards the issue of poverty reduction throughout the developing world. The persistence of mass poverty and hunger is a serious threat to macro-economic stability and long-term development. One of the key steps along the pathway to sustainable development is efficient targeting of the poor. Therefore, the motivation for this research stems from increasing interest showed towards the issue of targeting. This work builds on earlier research by the IRIS Center of the University of Maryland, but extends it through the use of methods for testing the models' robustness and out-of-sample validity.

This paper explores the use of proxy means tests to identify the poorest households in Uganda. The set of indicators used in our model includes variables usually available in Living Standard Measurement Surveys (LSMS). Proxy means tests use household socioeconomic indicators to proxy household poverty or welfare level. In addition to the Ordinary Least Square (OLS) method, the paper explores the use of Linear Probability Model (LPM), Probit, and Quantile regressions to select the best set of ten regressors for correctly predicting the household poverty status.

A further innovation of this research compared to the existing literature (Zeller et al., 2006; Zeller and Alcaraz V., 2005; Grootaert and Braithwaite, 1998; Grosh and Baker, 1995) is the use of out-of-sample validation tests to assess the predictive power and hence the robustness of the identified set of regressors using a different sample derived from the same population. To our knowledge, only Johannsen (2006) so far applied out-of-sample validation tests in the development of proxy means tools. Finally, we estimate the confidence interval out-of-sample using the bootstrap algorithm and the percentile method.

The paper is organized as follows. Section 2 reviews the data and methodology, whereas section 3 presents the empirical results. Section 4 concludes the work with observations on policy implications.

2. Data and Methodology

2.1 Data Collection

The IRIS center of the University of Maryland worked with NIDA, a survey firm that carried out a nationally representative household survey (Zeller and Alcaraz V., op cit). Two types of questionnaires were employed. The composite questionnaire enumerated indicators from many poverty dimensions. In order to measure absolute poverty, an LSMS-type household expenditure questionnaire was administered exactly 14 days after the interview with the composite questionnaire. The questionnaires were adapted to the country-specific context and can be downloaded at www.povertytools.org.

Two types of poverty lines were used, as outlined by the *Amendment to the Microenterprise for Self-Reliance and International Anti-Corruption Act of 2000* by US congress (USAID, 2005). According to that legislation, a household is classified as "very poor" if either (a) the household is "living on less than the equivalent of a dollar a day" ($1.08 per day at 1993 Purchasing Power Parity) — the definition of "extreme poverty" under the Millennium Development Goals; or (b) the household is among the poorest 50 percent of households below the country's own national poverty line.

The international 1 dollar a day poverty line yields a higher headcount index of "very poor" as compared to the alternative definition of the bottom 50 percent of the population below the national poverty line. Therefore, the international poverty line was used to differentiate the “very poor” and non-poor. Based on this, the poverty rate was estimated at 32.36%.

2.2 Model and Estimation Methods

2.2.1 Overview of Variable Set

As mentioned earlier, our model includes variables usually available in Living Standard Measurement Survey (LSMS). The choice of this model was motivated by the availability of LSMS data sets in many developing nations. Hence, the analysis could be easily replicated in other countries.

2.2.2 Estimation Methods: OLS, LPM, Probit, and Quantile Regressions

In order to perform out-of-sample tests, the initial sample (788 observations) was first split into two sub-samples in ratio 67:33. The larger sample or *calibration sample* (525 observations) was employed to identify the best set of variables and their weights, whereas the smaller sample or *validation sample* (263 observations) was used to test out-of-sample the prediction accuracy of the constructed tools and bootstrapped the confidence intervals. In the out-of-sample test, we therefore applied the set of identified indicators and their derived weights to predict daily per-capita expenditures in order to assess the robustness of the tool.

Four estimation methods were applied. These included: the Ordinary Least Square method (OLS), the Linear Probability Model (LPM), the Probit, and Quantile regressions.

All of the methods sought to identify the best set of ten regressors for predicting the household poverty status. For the OLS and LPM models, the MAXR routine of SAS was used to identify the set of best ten regressors that maximizes the model’s explained variance. Since it is not feasible to use the MAXR procedure for estimating the Quantile and Probit regressions, the ten regressors from the LPM and OLS models were introduced in the Probit and Quantile models, respectively. Strictly speaking, this approach is methodologically inconsistent. The OLS and LPM minimize the sum of square deviations from the mean and selected the best ten variables based on the MAXR routine and maximum explained variance, whereas the Probit regression uses the maximum likelihood estimation method. The Quantile regression minimizes the sum of absolute deviates from a given point of estimation and used an iterative procedure involving a series of regressions with the given set of ten regressors as identified by the MAXR routine of SAS in the OLS model to determine the optimal point of estimation that maximize the Balance Poverty Accuracy Criterion (Table 2).

Table 1 describes the final number of indicators by regression type.

Table 1. Initial indicator set by regression type

OLS	LPM	Probit	Quantile
MAXR routine	MAXR routine	(Best 10 from LPM)	(Best 10 from OLS)
92 (7)	92 (7)	10 (7)	10 (7)

Source: Survey data, described in Zeller and Alcaraz V. (2005). Number of control variables in brackets (control variables are listed in Table 5 in the Annex).

The Quantile and OLS regressions used the continuous dependent variable logarithm of daily per capita expenditures. The Probit and LPM models had as dependent variable a dummy variable that is coded one if the household is very-poor and zero otherwise. In other words, the Probit and LPM models estimate the probability of a household being below the poverty line.

To identify the *actual household poverty status* (very-poor and non-poor), the actual daily per capita expenditures was compared to the US$ 1.08 a day cut-off point. Households with less than US$ 1.08 daily per capita expenditures were classified as very-poor and those with higher daily per capita expenditures were deemed non-poor.

To determine the *predicted household poverty status* from the OLS and Quantile regressions, the predicted per capita expenditures was compared to the above cut-off point. The probability of being poor was compared to the standard 0.5 cut-off for the LPM and Probit regressions. In other words, a household is predicted as very-poor if its probability of being poor is more than 0.5 and non-poor otherwise.

The Quantile regression model was estimated with STATA package, whereas the OLS, LPM, and Probit models were estimated with SAS. In all the models, control variables that capture regional differences were also introduced. Obviously, the above models do not seek to identify the determinants of poverty, but select variables that can best predict about the current poverty status of a household. Therefore, a causal relationship should not be inferred from the results.

2.3 Accuracy Measures and Confidence Interval Approximation

2.3.1. Accuracy Measures

Seven ratios have been proposed by IRIS (2005) to assess the accuracy of a poverty assessment tool. In addition, this paper develops two performance measures for assessing the robustness of the tool: *change in accuracy and robustness ratio* (Table 2).

Table 2. Definitions of accuracy ratios

Accuracy Ratios	Definitions
Total Accuracy	Percentage of the total sample households whose poverty status is correctly predicted by the estimation model
Poverty Accuracy	Households correctly predicted as very-poor, expressed as a percentage of the total very-poor
Non-Poverty Accuracy	Households correctly predicted as not very-poor, expressed as percentage of the total number of not very-poor
Undercoverage	Error of predicting very-poor households as being not very-poor, expressed as a percentage of the total number of very-poor
Leakage	Error of predicting not very-poor households as very-poor, expressed as a percentage of the total number of very-poor
Poverty Incidence Error (PIE)	Difference between the predicted and the actual (observed) poverty incidence, measured in percentage points
Balanced Poverty Accuracy Criterion (BPAC)	Poverty accuracy minus the absolute difference between undercoverage and leakage, each expressed as a percentage of the total number of very-poor
Change in Accuracy	Difference between in and out-of-sample accuracy, expressed in percentage
Robustness Ratio	100 minus the absolute value of the change in accuracy

Source: Adapted from IRIS (2005)

The first five measures are self-explanatory. Undercoverage and leakage are extensively used to assess the targeting efficiency of policies (Valdivia, 2005; Ahmed et al., 2004; Weiss, 2004). The performance measure PIE indicates the precision of a model in correctly predicting the observed poverty rate. Positive PIE values indicate an overestimation of the poverty incidence, whereas negative values show the opposite. The balanced poverty assessment criterion BPAC considers three accuracy measures that are especially relevant for poverty targeting: poverty accuracy, leakage, and undercoverage. These three measures exhibit trade-offs. For example, minimizing leakage leads to higher undercoverage and lower poverty accuracy. Higher positive values for BPAC indicate higher poverty accuracy, adjusted by the absolute difference between leakage and undercoverage. In this paper, the BPAC is used as the overall criterion to judge the model’s accuracy performance. In the formulation of BPAC, it is assumed that leakage and undercoverage are equally valued. However, a policy-maker may give higher or lower weight to undercoverage compared to leakage. This is in principle possible by altering the weight for leakage in the BPAC formula.

As stated earlier, to assess the tool's robustness, two performances measures are applied: the change in accuracy and the robustness ratio. The change in accuracy for a given ratio (C. Accuracy) is computed as the difference between in and out-of-sample accuracy for that ratio, expressed in percentage (e.g. difference in poverty accuracy between calibration and validation samples in %). The robustness ratio is measured as 100 minus the absolute value of the change in accuracy; the higher the robustness ratio, the more robust the tool. A robustness ratio of 100 implies a perfectly robust tool, whereas a lower ratio indicates a less robust tool.

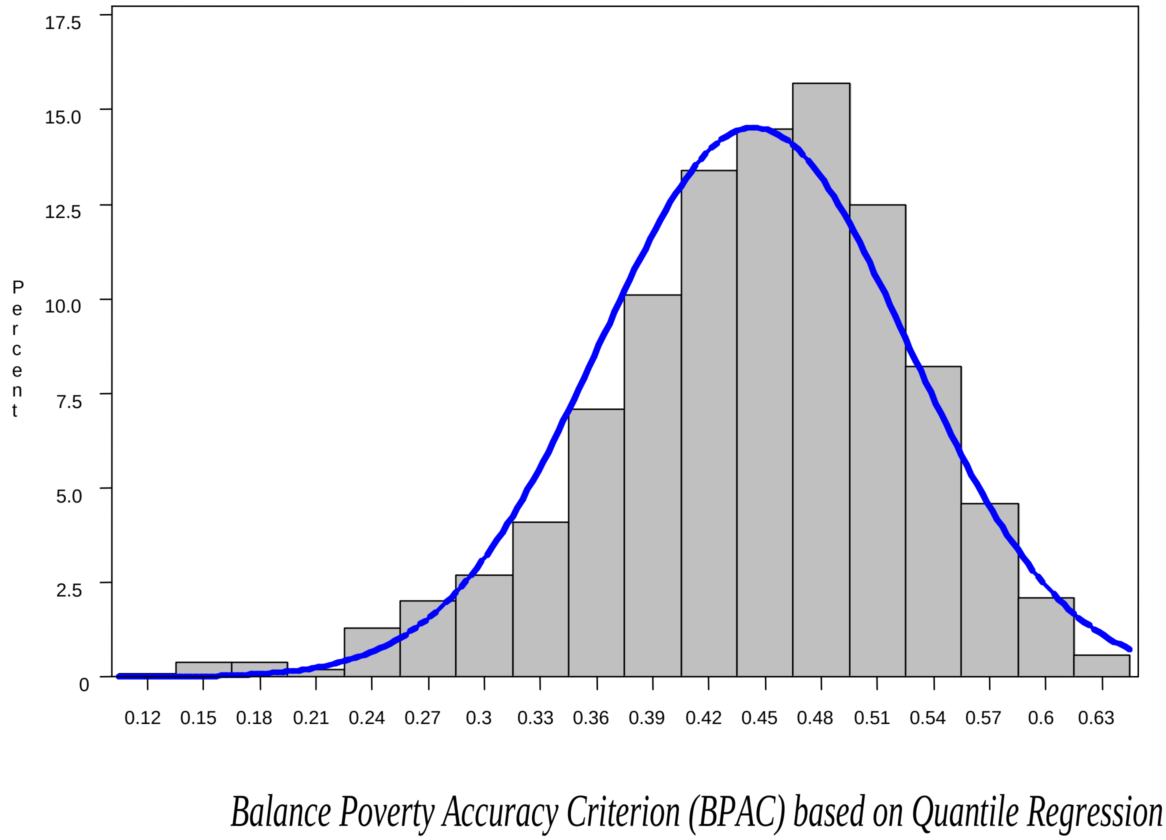
2.3.2 Confidence Interval Estimation

Confidence intervals for the accuracy ratios were estimated out-of-sample using the bootstrap technique. Approximate confidence intervals based on bootstrap computations were introduced by Efron in 1979 (Efron, 1987; Horowitz, 2000). Bootstrap is the statistical procedure which models sampling from a population by the process of resampling from the sample (Hall, 1994). Using the bootstrap approach, repeated random samples of the same size as the original sample were drawn with replacement using the validation sample (smaller sample of 263 observations). The set of identified indicators and their derived weights were applied to each resample to predict daily per-capita expenditures and calculate the accuracy ratios. These bootstrap estimates were then used to build up an empirical distribution for each ratio.

The reason for using the bootstrap technique for computing the confidence intervals stemmed from the fact that the accuracy ratios are aggregated measures. Traditional estimation of the confidence intervals based on standard error did not yield consistent results. Furthermore, unlike standard confidence intervals estimation, bootstrap does not make any distributional assumption about the population and hence does not require the assumption of normality. A thousand (1,000) new samples were used for the estimation.

Campbell and Torgerson (1999), state that the number of bootstrap samples required depends on the application, but typically it should be at least 1,000 when the distribution is to be used to construct confidence intervals. This large number of samples is required to ensure that the tails of the empirical distribution are filled. Graph 1 illustrates the BPAC distribution for the Quantile regression. This graph is superimposed with a normal curve.

Graph 1: Distribution of the accuracy ratios based on 1,000 samples



Source: Own computations based on data from Zeller and Alcaraz V. (2005).

After generating the bootstrap distribution, the percentiles of the distribution were computed and the values at the 2.5th and 97.5th percentiles were used as the limits for the interval at a 95% confidence level. This amounts to cutting the tails of the above distribution on both sides. The bootstrap algorithm and the percentile method provide the most consistent results.

3. Results and Discussions

3.1 Model Results

The present section discusses the model results and compares the performances of the regression methods applied. Table 3 describes the accuracy results. The full regression results and the indicator list, including their practicability rating are presented in Tables 5 through 9 in the Annex.

Table 3. Accuracy results

Uganda	Adj. R^2	Total Accur. (%)	Poverty Accur. (%)	Under-coverage (%)	Leakage (%)	PIE (% point)	BPAC (% point)
Poverty rate: 32.36%	Single-step methods -MAXR variable selection						
OLS	50.48						
In-sample		76.38	54.71	45.29	27.65	-5.71	37.06
Out-of-sample		69.58	48.24	51.77	42.35	-3.42	38.82
C. Accuracy		8.90	11.83	-14.31	-53.16	-40.11	-4.75
Robustness ratio		91.1	88.17	85.69	46.84	59.89	95.25
LPM	25.65						
In-sample		77.14	56.47	43.53	27.06	-5.33	40
Out-of-sample		71.86	52.94	47.06	40	-2.28	45.88
C. Accuracy		6.84	6.25	-8.11	-47.82	-57.22	-14.7
Robustness ratio		93.16	93.75	91.89	52.18	42.78	85.3
Probit							
In-sample		76.57	58.24	41.77	30.58	-3.62	47.06
Out-of-sample		70.72	52.92	47.06	43.53	-1.14	49.41
C. Accuracy		7.64	9.13	-12.66	-42.35	-68.51	-4.99
Robustness ratio		92.36	90.87	87.34	57.65	31.49	95.01
Quantile **P=47th**							
In-sample		74.86	60.59	39.41	38.24	-0.38	59.41
Out-of-sample		68.82	55.29	44.71	51.77	2.28	48.24
C. Accuracy		8.07	8.75	-13.45	-35.38	-700	18.81
Robustness ratio		91.93	91.25	86.55	64.62	-600	81.19

Source: Own computations based on data from Zeller and Alcaraz V. (2005). C. Accuracy denotes change in accuracy: difference between in and out-of-sample accuracy. P is the optimal point of estimation.

Table 3 suggests that in-sample; the total accuracy is estimated at about 76% for the OLS regression, whereas the poverty accuracy is estimated at about 55%. These results indicate that the method performs well in predicting not only the overall poverty status of the households, but also in correctly predicting the status of many poor. The BPAC amounts to about 37 percentage points. Undercoverage and leakage are moderately high, amounting to about 45% and 28% respectively. In other words, these results suggest that 45% of the poor households are predicted as non-poor and 28% of the non-poor are predicted as poor. On the contrary, the PIE is relatively low (about -6%) which implies a good prediction of the true poverty rate.

In-sample, the LPM method yields about 77% in terms of total accuracy and 57% for the poverty accuracy. Alike the OLS, these results show that the LPM algorithm performs well in estimating the overall poverty status, as well as the status of many poor. The BPAC is estimated at 40 percentage points which indicates a poor overall performance. Undercoverage and leakage are relatively moderate (44% and 27%), while the PIE is low (-5%) which shows a good prediction of the observed poverty rate.

The in-sample performances of the Probit regression are similar to the LPM results, except that the BPAC is much higher (47 percentage points). Overall, the Probit method performs better than the LPM regression, which in turn achieves slightly better results compared to the OLS regression.

With an optimal point of estimation identified at the 47^{th} percentile, the Quantile regression yields the highest in-sample poverty accuracy and BPAC. They are estimated at about 60% and 59 percentage points respectively. The total accuracy achieved is the lowest (about 75%). The PIE value nears zero (-0.38%) which implies an almost perfect prediction of the true poverty incidence. Furthermore, the Quantile regression yields the lowest undercoverage (about 39%). However, this estimation method also produces the highest leakage (about 38%). Using the BPAC to assess the method overall in-sample performance, the Quantile regression appears to be the first method, followed by the Probit and LPM. The OLS is the last best method. The same trend applies when considering the poverty accuracy, undercoverage, and PIE.

As concerns out-of-sample tests, the OLS method performs well in terms of robustness. The robustness ratios for the total and poverty accuracy are estimated at about 91 and 88 percentage points respectively. The ratio for the undercoverage amounts about 86 percentage points, whereas the same ratio is estimated at 95 percentage points for the BPAC. These results indicate that the moderate performances yielded by the OLS are quite robust with exceptions. The robustness ratio amounts about 47 percentage points for the leakage and 60 percentage points for the PIE, implying a poor performance.

The out-of-sample performances of the LPM are more robust in terms of total accuracy, poverty accuracy, undercoverage, and leakage only compared to the OLS results as indicated by their respective robustness estimates. The LPM results show a low robustness for the BPAC (about 85 percentage points) and PIE (about 43 percentage points). The results from the Probit regression follow a similar pattern as the LPM outputs with exceptions. Especially, the former yields a more robust ratio for the BPAC (about 95 percentage points). This result is as robust as the OLS performance. As for the Quantile method, the results indicate a poor robustness with respect to BPAC (81 percentage points). However, apart from the PIE, the Quantile regression displays a similar trend in robustness estimates compared to the remaining methods.

As a whole, these findings suggest that none of the methods consistently yields the most robust results for all estimates. Apart from the leakage and PIE, in general the robustness ratio is estimated at least 85 percentage points, which indicates that the results yielded are fairly robust, though there are differences from one method to the next. The only exception is the poor robustness in BPAC resulting from the Quantile regression. Overall, the OLS method yields the most robust results in terms of BPAC, followed by the Probit, the LPM, and then the Quantile regression.

Considering the BPAC only, the results in this paper seem to suggest the presence of a trade-off between accuracy and robustness. In other words, high in-sample BPAC is associated with a low out-of-sample BPAC. For example, the Quantile regression yields the highest in-sample BPAC, but the less robust tool. On the other hand, the OLS yields the most robust tool, but the lowest in-sample BPAC. The observed trade-off needs to be further substantiated through other country case studies. The next section presents the results from the confidence interval estimation.

3.2. Confidence Interval Approximation

Table 4 illustrates the results from the bootstrapped confidence intervals.

Table 4. Estimated Confidence intervals

	Ratio Type	Estimated Values			Confidence Intervals at 95% (1,000 Out-samples)		
		Predictions	**Mean**	**Median**	**Upper limit**	**Lower limit**	**Range (upper-lower)**
OLS	Total Accuracy	69.58	69.59	69.58	74.91	64.07	10.84
	Poverty Accuracy	48.24	48.26	48.05	59.55	37.09	22.46
	Leakage	42.35	43.64	43.35	61.91	28.43	33.48
	Undercoverage	51.77	51.74	51.95	62.91	40.45	22.46
	PIE	-3.42	-2.77	-2.85	3.80	-9.13	12.93
	BPAC	38.82	37.36	38.10	55.15	14.20	40.95
LPM	Total Accuracy	71.86	71.96	71.86	77.19	66.16	11.03
	Poverty Accuracy	52.94	53.04	53.33	63.07	41.71	21.36
	Leakage	40	40.99	40.48	57.23	27.06	30.17
	Undercoverage	47.06	46.96	46.67	58.29	36.93	21.36
	PIE	-2.28	-2.09	-2.28	3.80	-7.98	11.78
	BPAC	45.88	43.58	45.00	59.54	21.01	38.53
Probit	Total Accuracy	70.72	70.78	71.10	75.86	65.40	10.46
	Poverty Accuracy	52.92	52.98	53.01	63.29	41.52	21.77
	Leakage	43.53	44.64	43.90	62.09	29.63	32.46
	Undercoverage	47.06	47.02	46.99	58.48	36.71	21.77
	PIE	-1.14	-0.94	-1.14	5.32	-7.22	12.54
	BPAC	49.41	44.47	45.45	58.33	23.36	34.97
Quantile	Total Accuracy	68.82	68.86	68.82	74.14	63.12	11.02
	Poverty Accuracy	55.29	55.47	55.42	66.29	44.94	21.35
	Leakage	51.77	53.23	52.91	73.97	36.05	37.92
	Undercoverage	44.71	44.54	44.58	55.06	33.71	21.35
	PIE	2.28	2.58	2.66	9.13	-3.99	13.12
	BPAC	48.24	44.41	45.29	58.76	25.89	32.87

Source: Own computations based on data from Zeller and Alcaraz V. (2005).

It can be inferred from Table 4 that the interval length depends on the ratio type, but not on the estimation method applied. Interestingly, these results indicate that the estimated statistics are significantly different from zero, since none of the confidence limits are negative, except the PIE which takes the value of zero in the case of perfect prediction of the poverty incidence. The results also show that the out-of-sample predictions are close to the estimates of the mean and median of the distributions. Nonetheless, the interval lengths are relatively wide for all the ratios.

4. Conclusions

This research work analyzes the performances of different estimation methods in correctly predicting the household poverty status in Uganda. The variables used were derived from indicators usually available in Living Standard Measurement Survey (LSMS). The paper sought the best set of ten variables for identifying the poorest households in the country. In addition, out-of-sample validation tests were performed to assess the predictive power of the indicator sets. Finally, confidence intervals were estimated based on the bootstrap algorithm and the percentile method.

Findings suggest that the Quantile method yields the best in-sample performances, followed by the Probit and LPM regressions. The OLS is the last best method. With regard to out-of-sample validations, the trend is not straightforward. In general, the methods applied perform moderately well out-of-sample. However, none of the methods consistently yield the most robust results. The OLS and Probit regressions are more robust than the LPM and Quantile methods with respect to BPAC.

The main conclusion that emerges from this research is that measures of absolute poverty estimated with Quantile regression can yield fairly accurate in-sample predictions of absolute poverty in a nationally representative sample. On the other hand, the OLS and Probit perform better out-of-sample. Besides it complexity, the Quantile regression is less robust. The Probit may be the best alternative for optimizing both accuracy and robustness of a poverty assessment tool. However, running the Probit requires a prior run of the LPM using the MAXR routine of SAS to select the best ten variables.

The sets of indicators and their derived weights can be used in a range of applications. First, the sets can be viewed as potential, newly designed means-tested poverty assessment tools which could be used to identify the poorest households in the country. Especially, where poverty is pervasive and little gains are expected from geographic targeting (e. g. poverty mapping); direct identification of the poor should be preferred. Second, the sets can be used to assess eligibility to and the effects of a given social transfer scheme on the poor, and measure the impact on poverty (say Foster-Greer-Thorbecke class of poverty measures) under budget constraints. Third, the sets could be used to assess ex-post the poverty outreach of developments policies and the welfare impacts of agricultural developments projects targeted to those living below the chosen poverty lines in Uganda.

To confirm or reject the conclusions regarding the suitability of different regression methods, future research is needed to apply the regression and validation methods developed in this paper by using data sets from other countries.

Bibliography

Ahmed, A., Rashid, S., Sharma, M. and Zohir, S. (2004). Food aid distribution in Bangladesh: *Leakage and operational performance* Discussion paper No. 173. Washington, D.C.: International Food Policy Research Institute.

Campbell, M.K. and Torgerson, D. J. (1999). Bootstrapping: estimating confidence intervals for cost-effectiveness ratios. QJM: *International Journal of Medicine*, Vol. 92 (3):177-182.

Efron, B. (1987). Better bootstrap confidence intervals. *Journal of the American Statistical Association*, Vol. 82 (397): 171-185.

Grootaert, C. and Braithwaite, J. (1998). "Poverty correlates and indicator-based targeting in Eastern Europe and the Former Soviet Union." Poverty Reduction and Economic Management Network, Environmentally and Socially Sustainable Development Network. Washington D.C.: The World Bank.

Grosh, M. E. and Baker, J. L. (1995). "Proxy means tests for targeting social programs Simulations and speculation Working paper No 118. Washington D.C.: The World Bank.

Hall, P. (1994). Methodology and theory for the bootstrap. (PDF-File at http://wwwmaths.anu.edu.au/).

Horowitz, J. (2000). The Bootstrap. University of Iowa, Department of Economics (PDF-File available at http://www.ssc.wisc.edu)

IRIS. (2005). Note on assessment and improvement of tool accuracy. Mimeograph, Revised version from June 2, 2005. IRIS center, University of Maryland.

Johannsen J. (2006). Operational poverty targeting in Peru – Proxy Means Testing with non-income indicators Working paper No 30. International Poverty Center/UNDP

Sahn, D.E., and Stifel, D. C. (2000). Poverty comparisons over time and across countries in Africa. *World Development*, Vol. 28 (12), 2123-2155.

Sharma, S. (1996). Applied multivariate techniques. New York: John Wiley and Sons.

USAID (2005). Poverty assessment tools. AMAP (Available [online] at http://www.povertytools.org). Accessed November 10, 2005.

Valdivia, M. (2005). Is identifying the poor the main problem in targeting nutritional program? Discussion paper No. 7. Washington D.C.: World Bank.

Weiss, J. (2004). Reaching the poor with poverty projects: What is the evidence on social returns? Research paper No. 61. Tokyo: Asian Development Bank Institute.

Zeller, M., Sharma, M., Henry, C., and Lapenu, C. (2006). An operational tool for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia and Latin America in *World Development*, Vol. 34 (3), 446-464.

Zeller, M. and Alcaraz, V. G. (2005). Developing and testing poverty assessment tools: Results from accuracy tests in Uganda. IRIS Center, University of Maryland, College Park. (Available [online] at http://www.povertytools.org).

Annexes

Table 5. OLS regression results for the best set of indicators from Uganda

Uganda

Model significance F -Value = 32.43***

Adj. R^2 = 0.5048 Number of Observations = 525

	Regressor Set	Parameter Estimates	Standard Error	T-values
Control Variables	Intercept	7.373***	0.142	52.09
	Household size	-0.232***	0.029	-8.02
	Household size squared	0.010***	0.002	4.97
	Age of household head	-0.001	0.001	-0.74
	WESTERN location	-0.017	0.061	-0.28
	NORTHERN location	0.015	0.087	0.18
	EASTERN location	-0.099	0.067	-1.49
	URBAN location	0.234	0.122	1.93
Best 10 Indicators	Mobile phone ownership	0.236**	0.095	2.49
	Cooking fuel is charcoal or paraffin	0.404***	0.115	3.53
	Lighting source is gas lamp or electricity	0.384***	0.098	3.92
	Shoe ownership (spouse)	0.110**	0.053	2.07
	Number of hand hoes	0.049***	0.014	3.38
	Leather shoe ownership	0.065***	0.022	2.94
	Number of poultry	0.003	0.001	1.88
	Percentage of adults who can read only (% of size)	0.007***	0.002	3.13
	Room per person	0.112***	0.040	2.81
	Household head completed only secondary/post primary education	0.423***	0.010	4.25

Source: Own results based on data from Zeller and Alcaraz V. (2005). **** denotes significant at the 99% level. ** denotes significant at the 95% level.*

Table 6. LPM regression results for the best set of indicators from Uganda

Uganda

Model significance F-Value = 11.63***

Adj. R^2 = 0.2565 Number of Observations= 525

	Regressor Set	Parameter Estimates	Standard Error	T-values
Control Variables	Intercept	0.043	0.108	0.40
	Household size	0.121***	0.023	5.35
	Household size squared	-0.004***	0.001	-2.76
	Age of household head	0.001	0.001	0.56
	WESTERN location	0.096**	0.047	2.05
	NORTHERN location	0.122	0.067	1.82
	EASTERN location	0.089	0.051	1.74
	URBAN location	0.048	0.091	0.53
Best 10 Indicators	Household had access to formal loan in the past	-0.129	0.087	-1.47
	Cooking fuel is charcoal or paraffin	-0.218**	0.085	-2.58
	Shoe ownership (Head)	-0.113***	0.041	-2.75
	Household ownership of a withdrawable savings account	- 0.123	0.066	-1.88
	Number of literate female adults	-0.058**	0.025	-2.28
	Number of males adults	-0.073***	0.026	-2.81
	Number of radios	-0.094***	0.031	-3.01
	Number of tire shoes	0.226	0.096	2.37
	Number of members who can read only	-0.050	0.026	-1.93
	Number of rooms per person	-0.043	0.031	-1.39

Source: Own results based on data from Zeller and Alcaraz V. (2005). **** denotes significant at the 99% level. ** denotes significant at the 95% level.*

Table 7. Probit regression results for the best set of indicators from Uganda

Uganda

Likelihood ratio:185.138***, Score: 147.30***, Wald: 109.731***

Number of Observations= 525

	Regressor Set	Parameter Estimates (MLE)	Standard Error	Wald Chi-Square
Control Variables	Intercept	-1.617***	0.464	12.169
	Household size	0.426**	0.092	21.453
	Household size squared	-0.016***	0.006	7.730
	Age of household head	0.006	0.005	1.697
	WESTERN location	0.354	0.188	3.536
	NORTHERN location	0.368	0.238	2.401
	EASTERN location	0.330	0.194	2.896
	URBAN location	0.485	0.506	0.920
Best 10 Indicators	Household had access to formal loan in the past	-0.558	0.389	2.050
	Cooking fuel is charcoal or paraffin	-2.004***	0.647	9.596
	Shoe ownership (Head)	-0.321**	0.155	4.280
	Household ownership of a withdrawable savings account	-0.472	0.307	2.364
	Number of literate female adults	-0.164	0.096	2.936
	Number of males adults	-0.236**	0.096	6.027
	Number of radios	-0.360***	0.124	8.489
	Number of tire shoes	0.701**	0.326	4.641
	Number of members who can read only	-0.164	0.092	3.143
	Number of rooms per person	-0.415	0.213	3.814

Source: Own results based on data from Zeller and Alcaraz V. (2005). **** denotes significant at the 99% level. ** denotes significant at the 95% level.* MLE denotes Maximum Likelihood Estimates.

Table 8. Quantile regression results for the best set of indicators from Uganda

Uganda

Number of Observations= 525

	Regressor Set	Parameter Estimates	Standard Error	T-values
Control Variables	Intercept	7.416***	0.153	48.52
	Household size	-0.272***	0.035	-7.77
	Household size squared	0.012***	0.003	4.54
	Age of household head	-0.001	0.002	-0.49
	WESTERN location	-0.010	0.058	-0.18
	NORTHERN location	0.002	0.067	0.03
	EASTERN location	-0.113	0.066	-1.71
	URBAN location	0.214	0.111	1.93
Best 10 Indicators	Mobile phone ownership	0.257***	0.077	3.33
	Cooking fuel is charcoal or paraffin	0.487***	0.105	4.64
	Lighting source is gas lamp or electricity	0.320***	0.079	4.06
	Shoe ownership (spouse)	0.171***	0.049	3.52
	Number of hand hoes	0.051***	0.017	2.94
	Leather shoe ownership	0.040	0.031	1.29
	Number of poultry	0.004**	0.002	2.08
	Percentage of adults who can read only (% of size)	0.008***	0.003	2.95
	Room per person	0.106	0.055	1.94
	Household head completed only secondary/post primary education	0.488***	0.137	3.55

Source: Own results based on data from Zeller and Alcaraz V. (2005). **** denotes significant at the 99% level. ** denotes significant at the 95% level.*

Table 9. Practicability of indicators

Indicator Set	*Estimation Methods*				*Practicability**
	OLS	*LPM*	*Probit*	*Quantile*	
Mobile phone ownership	X			X	1
Cooking fuel is charcoal or paraffin	X	X	X	X	1
Lighting source is gas lamp or electricity	X			X	1
Shoe ownership (spouse)	X			X	1
Number of hand hoes	X			X	2
Leather shoe ownership	X			X	1
Number of poultry	X			X	2
Percentage of adults who can read only (% of size)	X			X	3
Room per person	X	X	X	X	2
Household head completed only secondary/post primary education	X			X	1
Household had access to formal loan in the past		X	X		1
Shoe ownership (head)		X	X		1
Household ownership of a withdrawable savings account		X	X		2
Number of literate female adults		X	X		2
Number of males adults		X	X		2
Number of radios		X	X		2
Number of tire shoes		X	X		2
Number of members who can read only		X	X		2

Source: Own results based on data from Zeller and Alcaraz V. (2005). *Practicability: 1= very good; 2= good; 3= fair.