Targeting the Poor and Smallholder Farmers – Empirical Evidence from Malawi –

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Abstract

The recent international financial crisis and the steady decrease in development assistance have put many poor countries under increasing pressure to target more accurately their public spendings at the poor and the population in need. However, further progress is hampered by the lack of accurate and operationally reliable methods for identifying the targeted population affected by poverty. Therefore, this paper develops low cost and fairly accurate models for improving the targeting efficiency of development policies. Using household-level survey data from Malawi, this research applies various econometric methods along with out-of-sample tests to develop operational poverty targeting models for the country. Though there is a scope for further improvements, the results show that the developed models can considerably improve the poverty outreach of development policies compared to the currently used targeting mechanisms in the country. Likewise, this research can be replicated in other developing countries.

Keywords: poverty targeting, predictions, Malawi, out-of-sample tests
JEL: C01, C13, I32

1 Introduction

Lately, policy makers as well as international donors have begun to take concrete steps to direct their financial and technical support to those programs that have greater poverty outreach and withdraw resources from those that fail to reach the poor (ZELLER et al., 2006). While this is definitely a step in the right direction, further progress is hampered by the lack of low cost, accurate, and operationally reliable methods for targeting the poor and assessing whether a project, policy or development institution reaches the poor and the population in need (Ibid.). This paper seeks to fill this knowledge gap. We develop low cost, reasonably accurate, and simple models for targeting the poor and smallholder farmers in Malawi, one of the poorest countries in Sub-Saharan Africa with a poverty rate of 52.4% (NATIONAL STATISTICS OFFICE, 2005a).

Deeply entrenched poverty is a major obstacle to Malawi's development and growth. The country is mostly agricultural with over 80% of its population working in the primary sector (BENSON, 2002). Though small landing holding size is not synonymous with poverty, most of Malawi's poor are smallholder farmers with 0.51 hectare of land per household (IHS2 survey results). To target these poor and smallholder farmers, the Government of Malawi relies mainly on community-based targeting mechanisms in which village development committees and other community representatives identify program beneficiaries based on their assessment of the household living conditions. However, most of the country's development programs are poorly targeted at the population in need. According to the Malawi Second Integrated Household Survey (IHS2), 35% of the rural poor did not benefit from the Targeted Starter Pack (TIP)[1] of 2000/2001, while 62% of the non-poor wrongly received program benefits.

Likewise, researches by RICKER-GILBERT and JAYNE (2009) and DORWARD et al. (2008) suggest that the 2006/2007 Agricultural Input Subsidy Program (AISP) has been targeted to wealthier and politically connected farmers who would otherwise have purchased the fertilizer, causing substantial displacements on the fertilizer market. An evaluation of the AISP program indicates that 46% of the poor did not receive fertilizer vouchers, whereas 54% of the non-poor were wrongly targeted (DORWARD et al., 2008). Almost all interventions have targeting problems in the country (GOVERNMENT OF MALAWI and WORLD BANK, 2007). As a result, poverty has not been substantially reduced in the country since 1998 (NSO, 2005a). Furthermore, given the lack of progress during the past decade, Malawi is unlikely to achieve the target reduction in poverty and ultra-poverty by 50% between 1990 and 2015 (GOVERNMENT OF MALAWI and WORLD BANK, 2007).

Therefore, this research explores whether proxy means tests can improve the targeting of the poor and smallholder farmers in the country compared to the currently used methods. Proxy means tests use household socioeconomic indicators to proxy household poverty or welfare status. They have the merit of making replicable judgments using consistent and visible criteria (COADY et al., 2002) and are also simple to implement and less costly than sophisticated means tests[2]. Better targeting has become an imperative for many developing countries in the wake of structural adjustments under which Governments are under pressure to cut back enormously on public expenditures (CHINSINGA, 2005).

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1 The Targeted Starter Pack or Targeted Input Program (TIP) provided free agricultural inputs, such as fertilizers and seeds to qualified farmers.

2 Means tests directly measure household income to determine its welfare level. Due to the difficulties associated with such tests, they are largely reserved for industrialized countries. See COADY et al. (2002) and GROSH and BAKER (1995) for further details on means tests.

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

2 Data and Methodology

2.1 Data and Theoretical Framework

This research uses the Second Malawi Integrated Household Survey (IHS2) data[3]. The NATIONAL STATISTICS OFFICE (NSO, 2005b) of Malawi conducted the IHS2 with the assistance of the International Food Policy Research Insitute (IFPRI) and the World Bank. The survey covered 11,280 households and 51,288 individuals over an estimated population of 12,170,000 people. The sample was selected based on a two-stage stratified sampling selection which involved in the first stage the selection of the enumeration areas (EAs) based on a Probability Proportional to Size (PPS) sampling and in the second stage a random selection of 20 households per EA.

To stick with standard practice, we define poverty as a level of consumption and expenditure by individuals in a household which has been calculated to be insufficient to meet their basic needs. Furthermore, the distinction between exogenous and endogenous variables in the holistic causal chain of poverty is difficult to make in practice: feedback loops and endogeneity issues can be conceptualized virtually everywhere in this chain (GROOTAERT and BRAITHWAITE, 1998). However, since the purpose of a poverty assessment is to measure poverty (i.e., to identify and use highly significant, but easily measurable correlates of poverty) and not to analyze causal relationships, it is analytically permissible to measure primary causes (lack of entitlements, rights, and endowments) together with intermediate and final outcome variables in the consumption, production, and investment spheres of individuals and their households as possible indicators of poverty (ZELLER et al., 2006). Therefore, this research does not seek to identify the determinants of poverty, but select variables that can best predict the current poverty status of a household. A causal relationship should not be inferred from the results.

[3] We gratefully acknowledge the National Statistics Office of Malawi for providing us with the data.

2.2 Model Estimation Methods

2.2.1 Variable Selection

Initially, about 800 variables were prepared for the estimates based on the Malawi IHS2 dataset. However, only 98 practical indicators[4] were selected for further analyses in order to ensure an operational use of the models. The practicality refers to two criteria: *difficulty* and *verifiability* of indicators. Initially, variables that are difficult to measure, verify (for example, subjective or monetary variables), and compute were excluded from the set of available indicators.

All of the poverty indicators used to estimate the models are categorical variables. Categorical variables are easier to measure and less susceptible to measurement error than continuous variables. Furthermore, the use of categorical variables allows simplifying the model application on the field. The list of selected variables reflects different dimensions of poverty, such as demography, housing, education, and assets. These variables are usually available in LSMS data and most national surveys in developing countries. Hence the analysis can be replicated in other countries.

2.2.2 Estimating the Proxy Means Tests

Separate models were estimated for rural and urban areas because of substantial differences between both areas of the country. In order to perform the validation tests (confer section 2.3.2 for further details), the initial samples were first split into two sub-samples following the ratio 67:33. The larger samples or *calibration samples* were employed to estimate the models, i.e. identify the best set of indicators and their weights, whereas the smaller samples or *validation samples* were used to test out-of-sample the predictive accuracy of the models. In the out-of-sample tests, we therefore applied the set of identified indicators and their derived weights to predict the household poverty status. We followed in the sample split a two-stage stratified sampling selection process and PPS protocol in order to mimic the initial sample selection. This design ensures that all strata are adequately represented in the calibration samples. Table 1 describes the number of indicators and the sample size by model types.

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[4] The list of indicators was reduced to 79 in the urban model; some of the variables were not relevant in urban areas.

Table 1. Sample size by model types

Sub-samples	Rural model	Urban model	Total
Total sample size	9,840	1,440	11,280
- calibration (2/3)	6,560	960	7,540
- validation (1/3)	3,280	480	3,760
Number of indicators	98	79	-

Source: own calculations based on Malawi IHS2 data

Except for three, all of the indicators selected are ordinal. Therefore, before estimating the models, the association of each indicator with poverty (as measured by the national poverty line) was measured by the *spearman correlation test* (SAS INSTITUTE, 2003). After performing the tests, indicators that were strongly correlated with poverty[5], including the three nominal variables were considered for further analyses. The logit regression was applied to estimate the models and identify the best set of indicators out of the preselected variables. Logit or probit regression is commonly used in the literature on poverty assessment[6]. Likewise, binary regression is the preferred choice in credit scoring (MAYS, 2004).

The models used the actual household poverty status as determined by the national poverty line of 44.29 Malawi Kwacha (MK) per day as dependent variable. This variable was coded one if the household is non-poor (i.e. expenditures above MK44.29) and zero otherwise. In other words, the logit model estimated the probability of a household being above the poverty line.

The model is specified as follows:

$$\text{(1)} \qquad \rho_i(y_i = 1 | x_i) = \frac{1}{1+e^{-\eta_i}}$$

ρ_i is the probability of being non-poor, e is an exponential function, y_i is the poverty status variable,

$$\text{(2)} \qquad y_i = \begin{cases} 1 \ (non-poor) \ \ if \, \rho_i \geq cut-off \\ 0 \ (poor), \ otherwise \end{cases}$$

5 The first fifty indicators were selected based on the absolute values of their coefficients. All of the indicators were significantly associated with poverty at 1% level of error.

6 See for example BRAITHWAITE et al. (2000), ZELLER and ALCARAZI (2005), ZELLER et al. (2005), SCHREINER (2006).

η_i is the linear predictor,

(3) $$\eta_i = \beta_o + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i$$

$x_{ik}, k = 1....K$ *and* $i = 1....n$ is the set of categorical poverty predictors, including the control variables, β_o is the intercept term, $\beta_{1k}, k = 1...K$ are the parameter estimates, ε_i is the error term.

η_i, the estimated logit is given by:

(4) $$\ln\left(\frac{\hat{\rho}_i(y_i = 1|x_i)}{1 - \hat{\rho}_i(y_i = 1|x_i)}\right) = \hat{\beta}_o + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_k x_{ik}$$

A forward stepwise selection of variables was used based on the maximum "c" statistic along with judgment on potentially good poverty predictors with "c" as the area under the Receiver Operating Characteristic (ROC) curve. The higher the area of c, the higher the efficacy of the ROC to distinguish between two diagnostic situations (BAULCH, 2002). Previous applications of the "c" criterion to evaluate the accuracy of individual poverty indicators include SCHREINER (2006), BAULCH (2002) and WODON (1997) who applied the ROC curve in combination with probit or logit regression in a calibration sample only.

In addition to the "c" statistic, the criteria for the selection of indicators were based on ZELLER et al. (2006) and included practicability considerations regarding the ease and accuracy with which information on the indicators could be quickly elicited in an interview as well as considerations regarding the objectiveness and verifiability of an indicator. Likewise, variables that express similar relationships were screened to select the best. As stated by MAYS (2004), scorecard building is a combination of art and science. The policy analyst needs to exercise a good deal of judgment and common sense in evaluating the usefulness of different poverty indicators (BAULCH, 2002).

Previous researches show that in general, the higher the number of indicators, the higher the achieved accuracy[7]. Higher accuracy is often achieved at a cost of practicality and operational use. Therefore, we limited the number of regressors to the best ten set in order to balance the cost of data collection, practicality and ensure an operational use of the models[8]. Furthermore, most analysts favor the use of a maximum of ten

7 See for example ZELLER and ALCARAZI (2005) and ZELLER et al. (2005).

8 The best ten simply refers to the indicator set being selected given the "c", the practicality, and the maximum number of regressors used to fit the final model. It should not be misunderstood as a value statement that implies as being best for any of the targeting ratios in table 2.

regressors in an operational poverty targeting model. We controlled for agricultural development districts in the rural model in order to capture agro-ecological and socio-economic differences between regions. Likewise, in the urban model we controlled for the four major cities: Mzuzu, Zomba, Lilongwe and Blantyre.

After estimation, the model coefficients (parameter estimates) were transformed into non-negative integers in order to allow the linear predictor[9] or score to be positive and range from 0 (most likely poor) to 100 (less likely poor). Such a transformation is standard practice in credit scoring[10]. It ensures that the models developed are quick, easy, and simple to use by development practitioners, program managers, and non-specialists (see annex 3).

Having estimated a household's poverty score, the question arises as to what cut-off point to use to determine whether it is poor or not. Therefore, the score cut-off (optimal score) that maximized the BPAC (see section 2.3 for details) in the calibration sample was used to predict the household poverty status. In other words, a household is predicted as *poor* if its score is less than the optimal score cut-off and *non-poor* otherwise. This classification was crossed with the actual household poverty status. The result was then used to estimate the targeting performances of the models based on the measures described in section 2.3.

2.3 Accuracy Measures and Robustness Tests

2.3.1 Accuracy Measures

Different measures have been proposed in the literature to assess the accuracy of a poverty targeting model. This paper focuses on selected ratios which are especially relevant for poverty targeting (table 2).

The poverty accuracy is self-explanatory. Undercoverage and leakage are extensively used to assess the targeting efficiency of development policies (VALDIVIA, 2005; AHMED et al., 2004; WEISS, 2004). Poverty Incidence Error (PIE) indicates the precision of the model in correctly predicting the poverty incidence. Ideally, the value of PIE should be zero, implying that the predicted poverty rate equals the observed rate. Positive values of PIE indicate an overestimation of the poverty incidence, whereas negative values imply the opposite. PIE is particularly useful in measuring the poverty outreach of an institution that provides microfinance or business development services.

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9 The linear predictor is the log odds (equation 2). It is normally unbounded in logit models.

10 See for example SCHREINER (2006), MAYS (2004) and THOMAS et al. (2001).

Table 2. Selected accuracy ratios

Targeting ratios	Definitions
Poverty Accuracy	total number of households correctly predicted as poor, expressed as a percentage of the total number of poor
Undercoverage	error of predicting poor households as being non-poor, expressed as a percentage of the total number of poor
Leakage	error of predicting non-poor households as poor, expressed as a percentage of the total number of poor
Poverty Incidence Error (PIE)	difference between predicted and actual poverty incidence, measured in percentage points
Balanced Poverty Accuracy Criterion (BPAC)	poverty accuracy minus the absolute difference between under-coverage and leakage, measured in percentage points

Source: adapted from IRIS (2005)

Balanced Poverty Accuracy Criterion (BPAC) considers the poverty accuracy, undercoverage, and leakage because of their relevance for poverty targeting. 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. As mentioned earlier, the BPAC is arbitrarly used in this paper as the overall criterion to judge a model is accuracy performance. In the formulation of the 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 possible in principle by altering the weight for leakage in the BPAC formula.

2.3.2 Assessing the Predictive Power of the Models

Out-of-sample validation tests were performed to gauge the predictive power of the models using independent samples derived from the same population. The main purpose of the validations is to observe how well the models will likely perform when used to identify the poor on the field. Without such validations, the accuracy of the models on the field would be unknown. Therefore, the models developed were validated by applying the set of selected indicators, their weights, and the optimal score cut-offs to the validation sub-samples in order to predict the household poverty status.

Furthermore, the model robustness was assessed by estimating the prediction intervals using 1,000 bootstrapped samples. Unlike standard confidence interval estimation, bootstrap does not make any distributional assumption about the population and hence does not require the assumption of normality[11].

3 Targeting Accuracy of the Proxy Means Tests: Empirical Results

This section discusses the results of the estimations[12]. First, the accuracy performances of the models are presented, including the prediction intervals. Second, the ROC curves of the models are analyzed, followed by the sensitivity analyses. Finally, we explore the distribution of the model targeting errors.

3.1 Model Predictive Performances

Table 3 describes the model predictive performances. The poverty lines applied and the full regression results are shown in the annex. All of the coefficient estimates are highly significant. Their signs are consistent with expectations and economic theory.

Table 3. Model predictive performances

	Targeting ratios	Cut-off	Poverty accuracy (%)	Under coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
Models	Rural	37	**68.52** (66.1; 70.6)	**31.48** (29.4; 33.9)	**28.0** (25.3; 30.8)	**-1.64** (-3.5; 0.2)	**65.03** (59.7; 69.6)
	Urban	20	**63.96** (55.0; 72.3)	**36.04** (27.7; 45.0)	**36.94** (24.8; 52.0)	**0.21** (-3.5; 3.8)	**63.06** (42.9; 67.7)
Programs	TIP	-	**65.02**	**34.98**	**61.81**	-	-
	AISP	-	**54.00**	**46.00**	**54.00**	-	-

Bootstrapped prediction intervals in brackets. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion. AISP denotes Agricultural Input Subsidy Program. TIP denotes Targeted Input Program.

Source: own results based on Malawi IHS2 data plus excerpt from DORWARD et al. (2009)

Table 3 suggests that the rural model correctly identifies about 69% of the poor against 64% under the urban model. Consequently, the undercoverage is estimated at 31% for the former and 36% for the latter. These results indicate that either of the models would enable a policy maker or a program manager to concentrate targeted benefits on

11 See HALL (1994) and EFRON (1987) for further details on bootstrapped simulation methods.

12 For brevity reasons, only out-of-sample results are presented throughout this paper.

about 2/3 of poor households when applied in Malawi. This will maximize the effectiveness of limited resources. If, for example, the Malawian Government chooses to target all rural poor households with a cash transfer program and sets the appropriate budget, the poverty rate (percent of households) would be reduced by about 32% points from 47.13% to 14.84%. If it were to target only 50% of the rural poor, the poverty rate would be reduced by a sizable margin of about 16% points from 47.13% to 30.84%.

As concerns the inclusion error, the urban model yields a higher leakage of about 37% versus 28% under the rural model. These results indicate that a part of the benefits from e.g. a targeted transfer program would also be leaked to the non-poor as none of the models are perfect at poverty targeting. Leakage to the non-poor is not harmful per se. It may increase the politically supportable budget necessary for targeting. As stated by GELBACH and PRITCHETT (2000), a leakier bucket may be better for redistribution to the poor whereas conversely, fine targeting can undermine political support for an antipoverty program (RAVALLION, 2007). Nevertheless, it remains to be seen whether political support for poverty reduction can be weakened in Malawi, a country where more than 50% of the population are poor.

Furthermore, both models predict the poverty rate remarkably well as their estimated PIEs are very low; 0.21% and -1.64% points, respectively. The BPAC is set at 65% points under the rural model and 63% for the urban model. Compared to the rural model, the targeting performances of the urban model are low. This relatively low targeting performance may be explained by the low poverty rate in urban areas compared to rural areas: 25% versus 56%.

As concerns the bootstrapped simulations, the estimated ratios fall within the prediction intervals. With respect to the rural model, the width of the prediction intervals ranges within 10% points for any given ratio at 5% level of error. This small margin suggests that the model's predictive performances are quite robust. However, the urban model displays wider prediction intervals which indicate a less robust model. This result is explained by the lower size of the sample used to validate the model[13].

More importantly, table 3 suggests that the rural model performs better than the TIP and AISP programs. For example, the model covers about 69% of the poor against 65% under the TIP. Likewise, only 28% of the non-poor are wrongly targeted by the model compared to 62% for the TIP.

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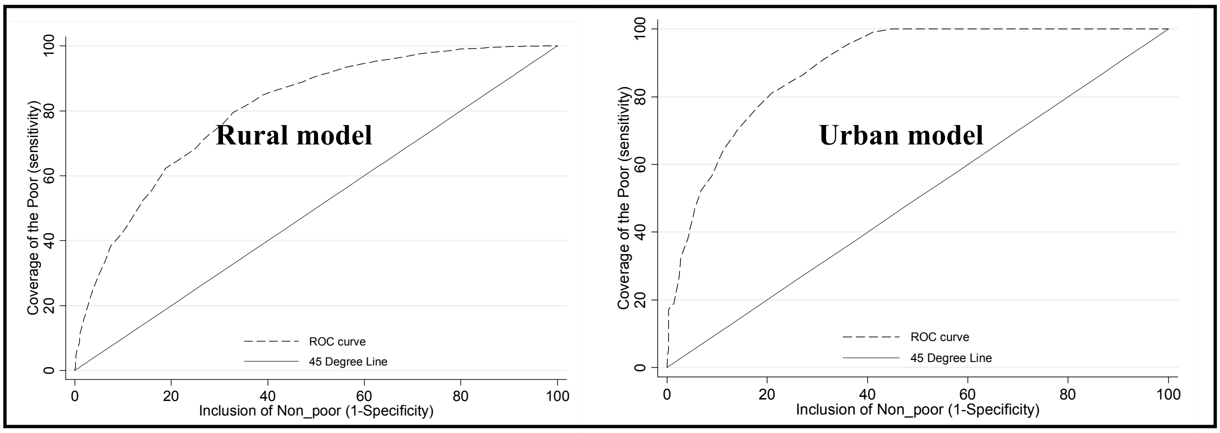
[13] Further results (not shown here) suggest that the mean and median estimates of the bootstrapped samples are very similar to the estimated targeting ratios.

3.2 Targeting Poverty using ROC Curves: Examples from Malawi

As stated earlier, the cut-off that maximizes the BPAC in-sample was used to estimate the model targeting performances. Depending on administrative, budgetary, or political reasons, however a policy maker or a program manager may set a different cut-off to decide on the number of poor a program or development policy should reach and ponder on the number of non-poor that would also be wrongly targeted. To demonstrate how this could be done in practice, we plot the ROC curves of the models (figure 1).

ROC curves are powerful means for measuring the trade-offs between the coverage of the poor (poverty accuracy) and the inclusion of non-poor (inclusion error) in an operational poverty targeting model[14]. The more the ROC curve is bowed towards the upper left of the graph, the better the model predicts the actual household poverty status. To our knowledge, apart from JOHANNSEN (2009), no research has applied the ROC curve in a validation sample.

Figure 1. ROC curves of the rural model (left) and urban model (right)



Source: own results based on Malawi IHS2 data

The ROC curves in figure 1 follow the same pattern with exceptions. In general, the curves show that the higher the coverage of the poor (sensitivity), the higher the inclusion of non-poor[15]. For example, the ROC curve of the rural model indicates that

[14] The coverage of the poor or poverty accuracy is also known as sensitivity, whereas the inclusion of non-poor or inclusion error is also termed as 1-specificity. It is defined as the error of predicted non-poor as poor, expressed in percent of non-poor. It differs from the leakage (table 1) which is expressed in percent of the poor.

[15] The 45° line on the graph shows a ROC curve with no ranking ability. This line yields the same coverage of the poor and inclusion of non-poor at any score cut-off.

covering 80% of the poor would lead to an inclusion of about 30% of non-poor households. Extending the coverage of the poor to 90% leads to more than 40% of the non-poor being wrongly included. This pattern illustrates the challenge of targeting the poor.

3.3 How sensitive are the Models to the Poverty Line?

In this section, we examine the sensitivity of the models to the choice of the poverty line. These simulations involved the calibration of the models to the international and extreme poverty lines (see annex 1). Table 4 shows the results of the simulations.

Table 4. Model sensitivity to the poverty line

Targeting ratios Models Poverty lines*		Cut-off	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
Rural	International	40	**84.52** (78.8; 82.9)	**15.48** (14.0; 17.1)	**18.87** (17.0; 21.1)	**2.23** (0.6; 3.8)	**81.13** (78.9; 83.0)
	Extreme	18	**46.13** (42.3; 49.8)	**53.87** (50.2; 57.7)	**38.13** (33.3; 44.0)	**-3.54** (-5.0; -1.9)	**30.39** (21.9; 39.6)
Urban	International	22	**76.30** (69.9; 82.5)	**23.70** (17.5; 30.1)	**27.17** (19.2; 36.9)	**1.25** (-2.5; 5.4)	**72.83** (62.0; 77.6)
	Extreme	8	**64.71** (43.4; 80.0)	**35.29** (20.0; 52.6)	**94.12** (57.6; 152.0)	**4.17** (1.7; 7.1)	**5.88** (-52.0; 42.0)

PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion. Prediction intervals in brackets. *See annex 1 for description of poverty lines.

Source: own results based on Malawi IHS2 data

Compared to previous results (table 3), table 4 shows that raising the poverty line to an international line of US$1.25 increases the coverage of the poor by about 16% points and 12% points under the rural and urban models, respectively. As a result, leakage is reduced by about 10% points for both models. The BPAC also increases by 16% points under the rural model and 19% points for the urban model. These results suggest a sizable improvement in the model targeting performances with about 85% of the poor correctly targeted in rural areas and 76% of the poor correctly identified in urban areas. Nearly, all of the poor are identified and covered in these simulations.

On the other hand, reducing the poverty line to an extreme line of MK29.31 disappointingly reduces the model targeting performances. For instance, the coverage of the rural poor is reduced by about 22% points. Likewise, leakage to the rural non-poor increases by 10% points. It seems therefore, fair to conclude that the higher the poverty line, the higher the coverage of the poor (and the lower the leakage) and vice versa. The following section analyzes the model targeting performances across regions.

3.4 Spatial Distribution of Targeting Errors

We disaggregate the model targeting errors across different regions of Malawi. Table 5 presents the distributions of these errors in rural areas.

Table 5. Spatial distribution of model targeting errors across rural Malawi

Regions Targeting errors	Karonga	Mzuzu	Kasungu	Salima	Lilongwe	Machinga	Blantyre	Ngabu
National poverty line								
Poverty rate (%)	60.00	46.56	36.00	40.12	36.72	59.84	50.16	53.33
Underco-verage (%)	26.04	35.57	31.25	20.29	35.77	52.74	11.53	14.84
Leakage (%)	11.46	28.86	35.42	46.38	42.31	6.53	34.28	40.63
International poverty line								
Poverty rate (%)	76.88	63.44	57.00	62.79	56.21	75.31	67.34	74.17
Underco-verage (%)	15.45	18.22	12.72	15.74	16.83	24.07	7.66	8.43
Leakage (%)	10.57	20.20	22.37	23.15	30.40	6.22	20.65	20.22
Extreme poverty line								
Poverty rate (%)	31.88	22.19	11.25	11.05	15.25	33.75	25.31	27.08
Underco-verage (%)	39.22	50.70	75.56	31.58	62.04	76.38	29.01	33.85
Leakage (%)	19.61	60.56	31.11	115.79	52.78	5.56	48.15	69.23

Source: own results based on Malawi IHS2 data

Table 5 suggests that targeting errors are not uniform across regions. Undercoverage levels are in higher Mzuzu, Kasungu, Lilongwe, and Machinga, while leakage rates are higher in Ngabu, Salima, Mzuzu, Lilongwe, and Blantyre. However, error levels are lower when the model is calibrated to the international poverty line, indicating improvements in targeting performances across regions. The opposite is true with respect to the extreme poverty line. Although not reported, similar trends emerge with regard to the urban model.

4 Conclusions

This research proposes simple, low cost, and reasonably accurate models for targeting the poor and smallholder farmers using household data from Malawi. The results suggest that the developped models performs better than previous development programs targeted at the poor in the country. Likewise, findings indicate that calibrating the models to a higher poverty line improves their targeting performances, while calibrating the models to a lower line does the opposite. A key feature of the models developped is that household scores can be easily and quickly computed on the field. The best indicators selected are categorical, objective, and fairly easy to verify. Nonetheless, an effective verification process (e.g. home visits, triangulation, etc.) is needed in order to ensure a fair screening process during the selection of program beneficiaries. To reduce error levels, the models can be combined with other targeting methods. Likewise, region-specific models could also be devised for each district of the country.

The models developed can be potential policy tools for Malawi. Apart from targeting the poor and smallholder farmers, they can be used to assess household eligibility to welfare programs, measure the impacts of development policies, assess the poverty outreach of microfinance institutions, estimate poverty rates, and monitor changes in poverty over time as the country cannot afford the costs of frequent household expenditure surveys. Though the models have proven their validity out-of-sample, there is a scope for further improvements: the observed patterns could be refined with additional validations across time as suitable data become available.

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Annexes

Annex 1. Malawi’s poverty rates by regions and poverty lines

Types of poverty lines	Poverty lines (MK*)	Poverty rate (in percent of people)			Poverty rate (in percent of households)		
		national	rural	urban	national	rural	urban
Extreme	29.81	26.21	28.66	8.72	19.94	22.08	5.95
National	44.29	52.40	56.19	25.23	43.58	47.13	19.67
International	59.18 (US $1.25 PPP)	69.52	73.59	40.26	61.04	65.20	33.08

MK denotes Malawi Kwacha or national currency. PPP stands for Purchasing Power Parity.
Source: Own results based on Malawi IHS2 data, CHEN and RAVALLION (2008), and WORLD BANK (2008).

Annex 2. Results of the maximum likelihood estimates (rural model)[1]

Likelihood ratio: 950419.735*** Wald Chi-square: 554730.601***
Score: 781671.495*** c-statistic = 0.837 Number of observations = 6560

	Standard	Wald			
Parameters	Estimate	Error	Chi-Square	Pr > ChiSq	Exp(Est)
Intercept	1.5498	0.0212	5340.5537	<.0001	4.710
Agricultural development district is Karonga	-0.1775	0.00817	472.2879	<.0001	0.837
Agricultural development district is Mzuzu	0.0643	0.00568	128.4419	<.0001	1.066
Agricultural development district is Kasungu	1.0299	0.00521	39023.5476	<.0001	2.801
Agricultural development district is Salima	0.0552	0.00592	87.0985	<.0001	1.057
Agricultural development district is Lilongwe	0.6642	0.00365	33125.4007	<.0001	1.943
Agricultural development district is Machinga	-0.7539	0.0038	39207.3345	<.0001	0.471
Agricultural development district is Blantyre	-0.4910	0.00385	16292.7820	<.0001	0.612
Agricultural development district is Ngabu (reference)					
Household size is two or less	2.7505	0.0047	337670.576	<.0001	15.651
Household size is three	0.8489	0.00355	57039.3650	<.0001	2.337
Household size is four	0.1165	0.00338	1186.4186	<.0001	1.124
Household size is five	-0.6271	0.00357	30914.1938	<.0001	0.534
Household size is six or seven	-1.1727	0.0034	115519.285	<.0001	0.310
Household size is eight or more (reference)					
Household head sleeps on bed and mattress	0.5739	0.00543	11175.4626	<.0001	1.775
Household head sleeps on bed and mat/bed alone	0.2921	0.00503	3372.9606	<.0001	1.339
Household head sleeps on mattress on the floor	0.0541	0.00749	52.2385	<.0001	1.056
Household head sleeps on mat (grass on the floor)	-0.2226	0.00379	3457.2988	<.0001	0.800
Household head sleeps on cloth/sack/floor (reference)					
Maximum class level ever attended by members is primary/nursery	-0.8112	0.0186	1901.2740	<.0001	0.444
Maximum class level ever attended by members is secondary	-0.2251	0.0186	146.6400	<.0001	0.798
Maximum class level ever attended by members is training/college	0.6733	0.0273	607.8646	<.0001	1.961
Maximum class level ever attended by members is university (reference)					
Household head owns no bicycle	-0.2754	0.00185	22265.7807	<.0001	0.759
Household head owns a bicycle (reference)					
House lighting fuel is collected firewood/grass	-0.9111	0.0114	6415.8002	<.0001	0.402
House lighting fuel is purchased firewood	-0.9687	0.0277	1224.5835	<.0001	0.380
House lighting fuel is candle	0.6149	0.0268	527.8702	<.0001	1.849
House lighting fuel is paraffin/diesel	-0.2468	0.0105	550.5214	<.0001	0.781
House lighting fuel is battery/dry cell/electricity (reference)					
House flooring material is sand	-0.6056	0.00626	9357.2213	<.0001	0.546
House flooring material is smooth mud/wood	-0.0747	0.00364	420.6285	<.0001	0.928
House flooring material is tile or cement (reference)					
Household owns no tape/cd player/HiFi	-0.2987	0.00274	11882.2099	<.0001	0.742
Household owns a tape/cd player/HiFi (reference)					
No household member sleeps under a bed net	-0.2096	0.00188	12378.3402	<.0001	0.811
A household member sleeps under a bed net (reference)					

Annex 2. Results of the maximum likelihood estimates (rural model) (cont.)

Household grew no tobacco in the past five seasons Household grew tobacco in the past five seasons (reference)	-0.2158	0.00221	9503.7619	<.0001	0.806
Household head cannot read in Chichewa language Household head can read in Chichewa language (reference)	-0.1562	0.00178	7673.3451	<.0001	0.855

[1] The results of the urban model are available upon request.

** denotes significant at the 95% level, *** denotes significant at the 99% level

Source: Own results based on Malawi IHS2 data.

Annex 3. Malawi's rural poverty model calibrated to the national poverty line[1]

Indicators	Values	Weight	Score
1. Where does the household live (agricultural development district)?	Blantyre Ngabu Karonga Salima, Mzuzu Lilongwe, Machinga Kasungu	0 1 2 4 8 10	
2. How many people live in the household?	Eight or more Six or seven Five Four Three Two or less	0 5 9 14 18 31	
3. What does the household head sleep on?	Floor/clock or sack on the floor Mat (grass) on the floor Mattress on floor Bed alone/Bed & Mat (grass) Bed & Mattress	0 3 5 7 8	
4. Does the household own a bicycle?	No Yes	0 4	
5. What is the maximum class level attended by household members?	Nursery/Primary Secondary University	0 4 8	
	Training/College	10	
6. What is the household source of lighting fuel?	Collected/purchased firewood or grass Paraffin/diesel Candle Electricity, gas or battery/dry cell	0 5 11 17	
7. What is the house flooring material made of?	Sand Smooth mud/wood Smooth cement/tile	0 4 9	
8. Does any household member sleep under a bed net?	No Yes	0 3	
9. Did the household grow tobacco in the past five cropping seasons?	No Yes	0 3	
10. Does the household own a tape/cd player, or HiFi?	No Yes	0 4	
11. Can the household head read in Chichewa language?	No Yes	0 2	
Household is deemed poor if its total score is less than 37	Total score		
Household poverty status: Poor ☐ Non-poor ☐			

[1] The results of the urban model are available upon request.

Source: Own results based on Malawi IHS2 data.