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Targeting the Poor and Smallholder Farmers
Empirical evidence from Malawi

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Discussion papers in this series are intended to stimulate discussion among researchers, practitioners and policy makers. The papers mostly reflect work in progress. This paper has been reviewed by Dr. Xavier Giné (World Bank) whom we thank for his valuable and pertinent comments.

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Abstract

This paper develops low cost, reasonably accurate, and simple models for improving the targeting efficiency of development policies in Malawi. Using a stepwise logistic regression (weighted) along with other techniques applied in credit scoring, the research identifies a set of easily observable and verifiable indicators for correctly predicting whether a household is poor or not, based on the 2004-05 Malawi Integrated Household Survey data. The predictive power of the models is assessed using out-of-sample validation tests and receiver operating characteristic curves, whereas the model's robustness is evaluated by bootstrap simulation methods. Finally, sensitivity analyses are performed using the international and extreme poverty lines.

The models developed have proven their validity in an independent sample derived from the same population. Findings suggest that the rural model calibrated to the national poverty line correctly predicts the status of about 69% of poor households when applied to an independent subset of surveyed households, whereas the urban model correctly identifies 64% of poor households. Increasing the poverty line improves the model's targeting performances, while reducing the poverty line does the opposite. In terms of robustness, the rural model yields a more robust result with a prediction margin ±10% points compared to the urban model. While the best indicator sets can potentially yield a sizable impact on poverty if used in combination with a direct transfer program, some non-poor households would also be targeted as the result of model's leakage. One major feature of the models is that household score can be easily and quickly computed in the field. Overall, the models developed can be potential policy tools for Malawi.

Keywords: Malawi, poverty targeting, proxy means tests, out-of-sample tests, bootstrap.

Targeting the Poor and Smallholder Farmers

Empirical evidence from Malawi

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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. While this is definitely a step in the right direction, further progress is hampered by the lack of low cost and operationally reliable methods for assessing whether a project, policy or development institution reaches the poor (Zeller et *al.*, 2006).

This paper seeks to fill this knowledge gap by developing low cost, reasonably accurate, and simple models for identifying the poor and smallholder farmers in Malawi. Most of the country previous development programs have been poorly targeted at the population in need. Almost all interventions have targeted problems in the country (Government of Malawi and World Bank, 2007). They suffer from limited beneficiary coverage and significant leakages to the non-poor (World Bank, 2007). As a result, poverty has not been reduced and the poverty rate remains above 50% in 2005 (National Statistics Office, 2005).

Therefore, this research explores the use of proxy means tests to identify the poor and smallholders farmers in the country. Proxy means tests use household socioeconomic indicators to proxy household poverty or welfare levels. The main objective of the tests is to infer Malawian poverty statuses without having to measure household consumption expenditures or income. Proxy-means tests are a simplification of the relationship often seen in survey data between household characteristics and its welfare level (Benson et *al.,* 2006). 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[3].

The logit (weighted) regression was used in a stepwise process to select the best set of operational indicators for correctly predicting the household poverty status. The model's

[3] Means tests directly measure household's 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.

predictive power was evaluated using out-of-sample validation tests and Receiver Operating Characteristic (ROC) curves. Furthermore, the model's robustness was assessed using bootstrap simulation methods. Finally, sensitivity analyses were conducted using the international and extreme poverty lines.

One major feature of the models is that household score can be quickly computed and its poverty status determined in the field. The set of indicators used in our models are usually available in World Bank's LSMS[4] data and from most household surveys in developing countries. Apart from targeting Malawi poor households, the models developed in this paper can be used in a wide range of applications, including the assessment of the welfare impact of development projects and the estimation and monitoring of poverty rates as the costs of frequent consumption expenditures survey cannot be justified for the country.

This paper is organized as follows. Section 2 reviews the data and methodology, including some theoretical considerations, 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[5]. The National Statistics Office (NSO, 2005) of Malawi conducted the IHS2 with the assistance of the International Food Policy Research Insitute (IFPRI) and the World Bank. The IHS2 was carried out from March 2004 through March 2005 and covered 11,280 households and 51,288 individuals over an estimated population of 2,731,346 households and 12,170,000 people. The sample was selected based on a two-staged stratified sampling selection process. First, the enumeration areas were selected within each district based on a Probability Proportional to Size (PPS) design. Second, 20 households were selected from each enumeration area based on a simple random sampling selection.

Compared to previous experiences, this survey is particularly suited to developing proxy means tests for three main reasons. First, it used an improved methodology for collecting and computing household consumption expenditures and poverty rates. Second, the survey covered a wide array of potential poverty indicators and thus offers an opportunity to

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[4] LSMS is the Living Standard Measurement Survey

[5] We gratefully acknowledge the National Statistics Office of Malawi (NSO) for providing us with the data.

develop highly accurate proxy means test models. Finally, the sample is representative at national as well as district levels.

Poverty in this research is defined as a level of consumption and expenditure by individuals in a household which has been calculated to be insufficient to meet their basic needs. It is generally agreed among analysts that expenditures (as an income proxy) are a more robust measure of poverty than income itself (Deaton, 1997). This definition is a standard, although narrow view of poverty (Benson, 2002). We adopt the consumption and expenditure-based perspective on individual and household welfare and on poverty mainly for two main reasons. First, the Government of Malawi and international organizations in the country use this definition for poverty targeting and measurement of development impact of rural and agricultural policies. Second, the concept of the monetary poverty line is also adopted by the first of the UN Millennium Development Goals. In view of the widespread use of monetary poverty lines with expenditure-based measures of poverty, the research pursues a policy-relevant objective by identifying indicator-based tools that can simplify the identification of rural poor, and measure welfare changes over time in poor populations.

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. 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.

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[6] were selected for further analyses to ensure an operational use of the models. The practicality refers to two criteria: *difficulty* and *verifiability*

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

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. These variables are easier to measure and less susceptible to measurement error than continuous variables[7]. Continuous variables were transformed into class variables. The choice of class boundaries was based on the distributional graphs, the coefficient of variation, and the distance between class means. These boundaries were set to ensure greater homogeneity within classes (low coefficient of variation) and higher heterogeneity between classes (large distance between class means). The list of selected variables reflects different dimensions of poverty, such as demographic, housing, education, and assets. These variables are usually available in LSMS data and most national surveys in developing countries. Hence the analysis could be replicated in other countries.

2.2.2 *Estimating the proxy means tests*

Separate models were estimated for rural and urban households for three main reasons. First the Malawi poverty study revealed different profiles for urban and rural households: there is a substantial difference between urban and rural areas in the country. Second, the interactions between the regions and other variables were found to be statistically significant in a national-level model. Third, the country-level model, when validated over urban households only, shows poor targeting performances (see Table 7 in the annex).

In order to perform the validation tests, each sample was first split into two sub-samples according to the ratio 67:33. The larger sample or *calibration sample* was employed to estimate the model, i.e. identify the best set of variables and their weights, whereas the smaller sample or *validation sample* was used to test out-of-sample the predictive accuracy of the model. In the out-of-sample tests, we applied the set of identified indicators and their derived weights to predict the household poverty status. The sample split followed 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. A simple random sampling split would not guaranty such representativity.

With the 67:33 split and the stratified sampling design, we put more emphasis on the model's calibration than validation. Furthermore, the continued representativity of the calibration samples was assessed by testing the differences in estimates across the samples and

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[7] Furthermore, the use of categorical variables allows simplifying the model's application on the field.

the full datasets. The results of the tests show no statistically significant difference between both sets. Therefore, the calibration samples are as representative as the full datasets.

After performing the sample split, the household weight was readjusted to reflect the new inflation rates in the calibration samples. In order to account for the importance of each household in the total population, the subsequent regressions were weighted using these new household weights. The weight adjustment however, was not necessary in the validation sub-samples because the weight is not needed to predict the out-of-sample accuracy of the models. Obviously, the same level of accuracy cannot be guaranteed in such smaller samples. Table 1 describes the number of indicators and the sample size by model type.

Table 1. Sample size by model type

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 national poverty line) was measured by the *spearman correlation test*. The spearman correlation test is a non-parametric test of association between two ordinal variables. It is appropriate only when both variables lie on an ordinal scale (SAS Institute, 2003). The spearman correlation coefficient ranges from -1 to 1 with values close to 1 or -1, indicating a stronger positive or stronger negative correlation between both variables respectively. The spearman test does not impose any normality assumption over the distribution of the variables. After performing the test, all of the indicators were ranked based on the absolute value of their coefficients. The first fifty indicators[8] (about one-half of the total number of indicators), including the three nominal variables were selected for the regression analyses. This screening is the first step towards the selection of indicators strongly associated with poverty, an important step to ensure accuracy in predictions.

The logit regression was applied to estimate the models and identify the best set of variables. Logit or probit regression is commonly used in the literature on poverty assessment[9]. Likewise, binary regression is the preferred choice in credit scoring (Mays, 2004).

[8] All of the indicators were significantly associated with poverty at 1% level of error.

[9] See for example Braithwaite et *al.* (1998); Zeller and Alcaraz V. (2005); Zeller et *al.* (2005); Schreiner (2008).

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 regression is of the form:

$$\mu_i\,(yi=1) = 1/(1 + e^{-}\eta_i) \qquad \mathbf{1}$$

$$\eta_i = \text{Log}\,[\mu_i/(1-\mu_i)] = ß_o + x_i\,.ß_i + \epsilon_i \qquad \mathbf{2}$$

μ_i is the probability of being non-poor;

y_i is the poverty status variable, $y_i = \begin{cases} 1 \text{ if } \mu_i > \text{cut-off} \\ 0 \text{ otherwise} \end{cases}$

η_i is the linear predictor or the log odds;

x_i ($x_{1,}$ $x_{2,}$ $x_3\ldots$, x_n) is a vector of regressors, all categorical variables;

$ß_o$ is the intercept term;

$ß_i$ is a vector of regression coefficients;

ϵ_i is the random error term.

The model was fitted with the maximum likelihood method. 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 (2008), Baulch (2002), and Wodon (1997) who applied the ROC curve in combination with logistic 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 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[10]. 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[11]. Furthermore, most analysts favor the use of a maximum of ten regressors in an operational poverty targeting model. We controlled for agricultural development districts in the rural model in order to capture agro-ecological and socioeconomic differences between regions. The inclusion of such variables also captures the effects of omitted variables, as well as the effects of other unobservable factors in the model. Likewise, in the urban model we controlled for the four major cities: Mzuzu, Zomba, Lilongwe, and Blantyre. The omission of such control variables would result in less accurate parameter estimates and hence low targeting performances.

After estimating the models, the logit coefficients were transformed into non-negative integers in order to allow the linear predictor[12] 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[13]. It ensures that the score is easy to understand and compute. The most important in rescaling the score is that its ordinal ranking is preserved. The linear predictor was used instead of the predicted probability of being non-poor because the former expresses a linear and simpler relationship between the score and the best indicators. The latter can only be derived through complex computations involving logarithmic and exponential functions, which are harder to perform when identifying poor households on the field. The transformation led to loss in the model's performance. However, the accuracy lost from the coefficient transformation is very low (see Tables 8 and 9 in the annex), especially when the model is calibrated to the national and international poverty lines. Therefore, the transformation does not compromise the validity of the models.

Once the models are developed, household score can be computed and its poverty status predicted. However, a cut-off score - a score below which a household is deemed poor - is needed to classify the households as poor or non-poor. The cut-off that maximizes the Balanced Poverty Accuracy Criterion (BPAC) in-sample (see section 2.3 for details) was chosen as the optimal cut-off for classification out-of-sample. In other words, a household is predicted as *poor*

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[10] See for example Zeller and Alcaraz V. (2005) and Zeller et *al.* (2005).

[11] 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.

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

[13] See for example Schreiner (2008), Mays (2004), and Thomas et *al.* (2001).

if its score is less than the optimal score cut-off and *non-poor* otherwise. This classification was used in a cross tabulation with the actual household poverty status. The two-by-two cross-table was then used to calculate different performance measures as 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 on poverty targeting to assess the accuracy of a poverty assessment tool. This paper focuses on selected ratios which are especially relevant for poverty targeting (Table 2).

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	Poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points

Source: Adapted from IRIS.

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). The 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 underestimation 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.

The Balanced Poverty Accuracy Criterion (BPAC) considers the above accuracy measures 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. In this paper, the BPAC is used as the overall criterion to judge the model’s accuracy performance. In the formulation of the BPAC, it is assumed that leakage and undercoverage are equally valued. For example, Ravallion (2007) found it more credible to value both measures in a characterization of a policy problem. However, a policymaker may give higher or lower weight to undercoverage compared to leakage, which is possible in principle by altering the weight for leakage in the BPAC formula.

2.3.2 Assessing the predictive power and the model's robustness.

Out-of-sample validation tests were performed to gauge the predictive power and the robustness of the models and ascertain their predictive potential. The main purpose of the validation is to observe how well the models predict the poor and non-poor in an independent sample derived from the same population. A model with high predictive power (high poverty accuracy and low leakage) not only in the calibration sample, but also in validation sample is relevant for reaching most of the poor households. Therefore, the models developed were validated by applying the set of selected indicators and their weights and the optimal score cut-off to the validation sub-samples in order to predict the household poverty status.

Furthermore, the model's robustness was assessed by estimating the prediction intervals of the targeting ratios out-of-sample using bootstrapped simulation methods. 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 validation sub samples were drawn with replacement. The set of identified indicators and their derived weights were applied to each resample to predict the household score, its poverty status, and estimate the accuracy ratios. These bootstrap estimates were then used to build up an empirical distribution for each ratio. 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 estimations. 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. Figure 1 illustrates the distribution of the poverty accuracy for 1,000 samples for the best ten indicator set. This graph is superimposed with a normal curve.

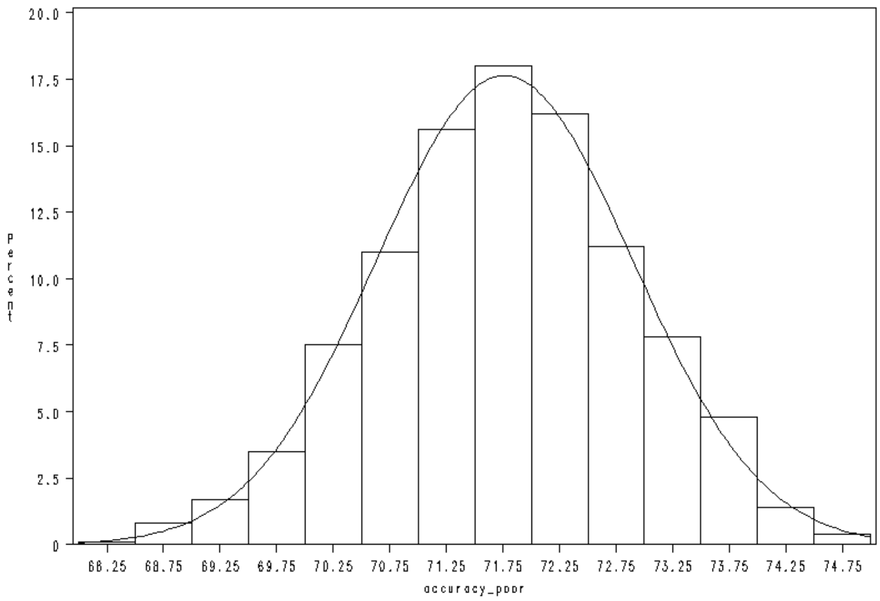

Figure 1: Bootstrapped distribution of the poverty accuracy (rural model).
Source: Own results based on Malawi IHS2 data.

After generating the bootstrap distribution, 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.

3. Targeting Accuracy of the Proxy Means Tests: Empirical results

This section discusses the out-of-sample performances of the models[14]. First, Table 3 gives an overview of the poverty lines and rates applied. Second, the accuracy performances of the models are presented, including the prediction intervals. Third, the ROC curves of the models are analyzed, followed by the sensitivity analyses. Finally, we explore the distribution of the model's targeting errors.

Table 3. Malawi poverty rates by region and poverty line (as of 2005)[15]

Types of poverty line	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	52.4	56.19	25.23	43.58	47.13	19.67
International	59.175 (US $1.25 PPP)	69.52	73.59	40.26	61.04	65.20	33.08

Source: Own results based on Malawi IHS2 data, Chen and Ravallion (2008), and World Bank (2008). MK denotes Malawi Kwacha or national currency. PPP stands for Purchasing Power Parity.

[14] For brevity reasons, only out-of-sample results are presented throughout this paper.
[15] These rates differ slightly from the official statistics because of errors in the weights of the IHS2 report.

As shown in Table 3, the poverty rate in Malawi is estimated at 52.4% under the national poverty line of MK44.29. In other words, more than half the population is unable to meet their basic needs. However, the poverty rate varies considerably between urban and rural areas. Following Chen and Ravallion (2008), the international poverty line of US$1.25 was used. Converted to Malawi Kwacha (MK) using the 2005 Purchasing Power Parity (World Bank, 2008), the international poverty line is equivalent to MK59.175 per day. Under this line, the national poverty headcount is estimated at 69.52%. This line hides sizeable differences between urban and rural areas. The extreme poverty line is defined as the line under which the poorest 50% of the population below the national poverty line are living. This line was set at MK29.31. Under the extreme poverty line, 26% of Malawians are very poor. These poverty rates are lower when expressed in percent of households. Section 3.1 presents the model's targeting performances.

3.1 Model's predictive performances

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 that maximized the BPAC in the calibration sample was applied to the validation sample to predict the household poverty status. Table 4 describes the model's predictive performances at these optimal cut-offs. Most of the coefficient estimates are highly significant. Their signs and size are consistent with expectations and economic theory. The full regression results are shown in Tables 10 and 11 in the annex.

Table 4: Model's predictive performances

Targeting ratios / Models	Cut-off	Poverty accuracy (%)	Under coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
Rural	37	68.52	31.48	28.0	-1.64	65.03
Urban	20	63.96	36.04	36.94	0.21	63.06

Source: Own results based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

Table 4 suggests that the rural model correctly identifies about 69% of poor households, against about 64% for 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 program manager to concentrate benefits on 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 direct transfer program and sets the appropriate budget, the poverty rate 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% for 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 is poor. Both models outperform the *Free Seed Distribution and Fertilizer Subsidy Program of 2000/2001* (also known as Starter Pack or Targeted Input Program) which yields a poor targeting efficiency. Though the program was explicitly targeted at poor households, its undercoverage and leakage are deceptively high and were estimated at 38% and 60%, respectively.

Furthermore, both models predict the poverty rate remarkably well as their estimated PIE is very low; 0.21% and -1.64% points, respectively. The BPAC is set at 65% points for 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 the urban area as compared to the rural area; 20% versus 47%. This result may also be due to the greater variability in the welfare indicator for urban households and between different urban centers in Malawi. The variance estimates of the welfare indicator support this argument. Nonetheless, even though undercoverage and leakage are high in urban areas, these errors amount to relatively small number of households; less than 15% of the Malawian population lives in urban areas. As shown in section 3.3, calibrating the urban model to a higher poverty line improves its targeting performances. Likewise, selecting less practical indicators could improve the model's targeting accuracy as indicated by previous researches[16]. However, the use of such indicators has to be weighted against the lost in practicality that will result.

Having validated the models in an independent sample, the question that arises then is: what is the prediction intervals associated with such targeting performances? To answer the

[16] See for example Zeller and Alcaraz V. (2005) and Zeller et *al.* (2005)

question, Table 5 illustrates the prediction intervals of the model's performances using bootstrapped simulations.

Table 5. Bootstrapped prediction intervals

Models	Targeting ratios	Location estimates		95% level of prediction		
		Mean	Median	Lower limit	Upper limit	Width (upper-lower)
Rural	Poverty Accuracy	68.44	68.48	66.11	70.6	4.49
	Leakage	28.03	28.05	25.30	30.84	5.54
	Undercoverage	31.56	31.52	29.43	33.89	4.46
	PIE	-1.67	-1.68	-3.45	0.17	3.62
	BPAC	64.86	64.88	59.67	69.58	9.91
Urban	Poverty Accuracy	64.15	64.17	55.04	72.32	17.28
	Leakage	37.45	36.84	24.78	52.00	27.22
	Undercoverage	35.85	35.83	27.68	44.96	17.28
	PIE	0.29	0.21	-3.54	3.75	7.29
	BPAC	57.35	58.04	42.92	67.68	24.76

Source: Own results based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

Table 5 indicates that the estimated mean and median of the bootstrapped samples are very close to the predicted performances in Table 4. Likewise, all of the estimated ratios in Table 4 range within the prediction intervals. The results of the rural model show that the width of the prediction intervals ranges within a maximum of 10% points for any given ratio at 5% level of error. This small margin suggests that the model's predictive performances are quite robust. As concerns the urban model, a different trend applies. The prediction intervals are wider, indicating a less robust model. This result is explained by the lower size of the sample used to validate the model as shown in Table 1.

As stated earlier, the cut-off that maximizes the BPAC in-sample is explicitly used to judge the model's overall targeting performance. However, a policymaker may set a different cut-off using the ROC curve to decide on the number of poor a program should reach and ponder on the number of non-poor that would be incorrectly targeted. To demonstrate how this could be done in practice, we present in section 3.2 the ROC curves of the models.

3.2 Targeting poverty using ROC curves: Examples from Malawi.

We plot the ROC curves out-of-sample to estimate the model's aggregate predictive power. The ROC curve shows the trade-offs between the coverage of the poor (poverty accuracy) and the inclusion of non-poor (inclusion error)[17] at different score cut-offs across the predicted score spectrum in the validation sample. To our knowledge, apart from Johannsen (2007), no research has applied the ROC curve in a validation sample.

The more the ROC curve is bowed towards the upper left of the graph, the better the model predicts the actual household poverty status. In addition to the ROC curves, we graph the BPAC curves out-of-sample. Figures 2 and 3 show the ROC curves which portray the ability of each model to distinguish between the poor and non-poor at possible cut-offs along the predicted score spectrum.

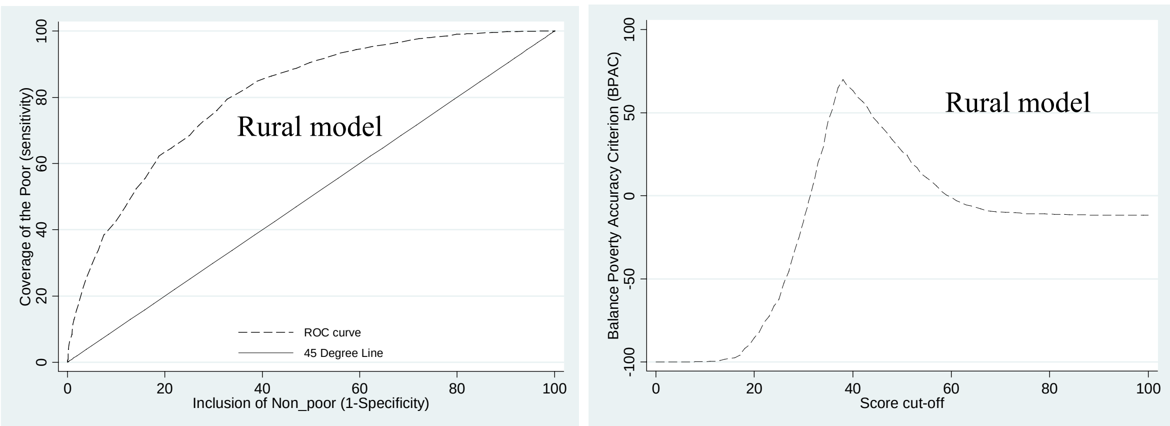

Figure 2: ROC curve (left) and BPAC curve (right) of the rural model (out-of-sample).
Source: Own results based on Malawi IHS2 data.

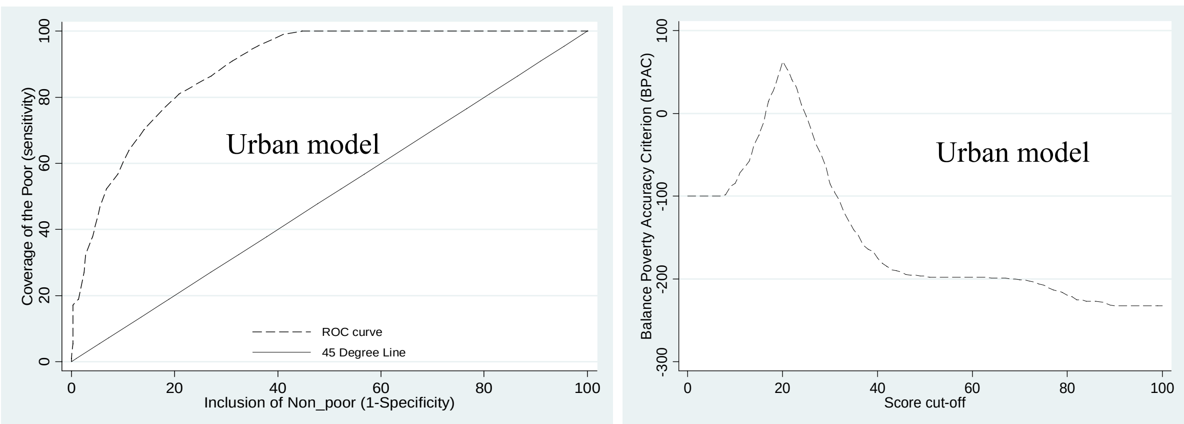

Figure 3: ROC curve (left) and BPAC curve (right) of the urban model (out-of-sample).
Source: Own results based on Malawi IHS2 data.

[17] 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 2) which is expressed in percent of the poor.

The ROC curves in Figures 2 and 3 show that the higher the coverage of the poor (sensitivity), the higher the inclusion of non-poor[18]. For example, the ROC curve of the rural model indicates that a coverage of 80% of the poor would lead to an inclusion of about 30% of the 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 trade-off between the coverage of the poor and inclusion of non-poor along the predicted score spectrum.

Both ROC curves follow the same pattern with exceptions. While the curves are monotonically increasing, their shape depends on the performances underlying each model used to predict the poverty status of the households. In the relevant band of sensitivity from 70% to 90%, the inclusion error ranges from about 22% to 50% for the rural model and from about 18% to 30% for the urban model.

It is interesting to note that the rural model maximizes its BPAC out-of-sample at a cut-off of 38 (right panel of Figure 2), whereas the urban model reaches its highest BPAC at a cut-off of 20 (right panel of Figure 3). The latter is identical to the optimal in-sample cut-off used to classify the urban households out-of-sample, whereas the difference between both cut-offs is just one in the case of the rural model. These results indicate that the cut-offs derived from the calibration samples are exceptionally robust out-of-sample, converging towards the out-of-sample optima[19]. Tables 12 and 13 in the annex present the transformed models as they would appear on the field.

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 described in Table 3. Since the dependent variable in the model - the household poverty status - is affected by the poverty line chosen, the logit regression, including the selection of indicators was re-estimated for both lines and models. Table 6 shows the results of the simulations.

[18] 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.
[19] The same conclusion emerges when the models were calibrated to the international and extreme poverty lines.

Table 6. Model's sensitivity to poverty line

Models	Targeting ratios / 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** (0.55; 3.81)	**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; 5.42)	**72.83** (62.0; 77.6)
	Extreme	8	**64.71** (43.4; 80)	**35.29** (20; 52.6)	**94.12** (57.6; 152)	**4.17** (1.67; 7.08)	**5.88** (-52; 42.04)

Source: Own results based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion. Prediction intervals in brackets. *See Table 2 for description of poverty lines.

Compared to the results in Table 4, Table 6 shows that raising the poverty line to US $1.25 (MK59.175 PPP) increases the coverage of the poor by about 16% points and 12% points for the rural and urban models, respectively. As a result, leakage is reduced by about 10% points for both models. The BPAC has also increased by 16% points for the rural model and 19% points for the urban model. These results suggest a sizable improvement in the model's targeting performances with about 85% of the poor households correctly targeted in the rural area and 76% of the poor households correctly identified in the urban area. Nearly, all of the poor households are identified and covered in these simulations.

On the other hand, reducing the poverty line to MK29.31 disappointingly reduces the model's targeting performances. For instance, the coverage of the poor is reduced by about 22% points for the rural model, but by less than 1% points for the urban model. Similarly, the leakage is increased by 10% points for the former, but by about 57% points for the latter. These results may be explained by the higher international and the lower extreme poverty lines. Therefore, increasing the poverty line allows picking more poor households, while reducing the poverty line does the opposite.

However, the ROC curves of models calibrated to the three poverty lines show a mixed pattern of the model's aggregate predictive power (see Figure 5 in the annex). The following section analyzes the targeting errors across poverty deciles.

3.4 Targeting error distribution

As we have seen in the previous sections, irrespective of the poverty line applied, the models yield targeting errors, though the errors decrease with increasing poverty line. This is due to the inherent model estimation error. While it is unsatisfactory to undercover poor households or wrongly target the non-poor, the error would be less severe if indeed those who are excluded are the least poor or those who are incorrectly targeted are the least rich households. To confirm this, we look at the distribution of the model's undercoverage and leakage by deciles of actual consumption expenditures for the three poverty lines (Figure 4).

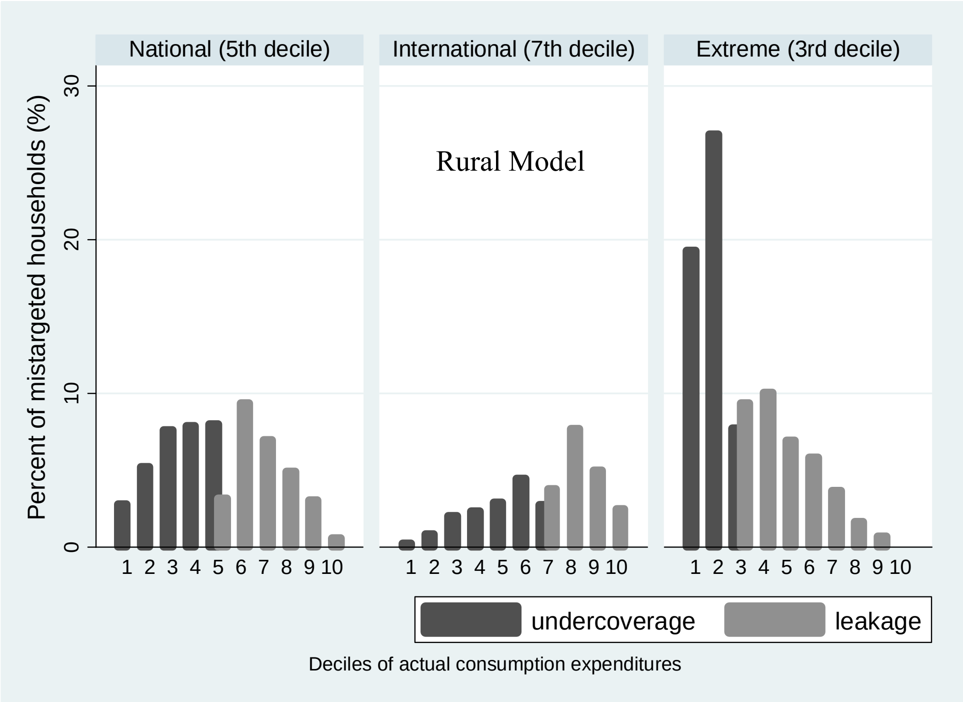

Figure 4: Targeting error distribution by decile of consumption and poverty line.
Source: Own results based on Malawi IHS2 data.

Figure 4 shows that when calibrated to the national poverty line, poor households who are undercover are heavily concentrated among those just under the line in the 5th decile rather than at the very bottom of the welfare distribution, while those who are incorrectly targeted are also heavily concentrated among those just over the national poverty line rather than at the top of the distribution. The same trend applies to the international and extreme poverty lines. These results suggest that the model performs quite well in terms of the poor households who are incorrectly excluded and the non-poor who are wrongly targeted; covering most of the poorest deciles and excluding most of the richest ones.

Further simulations based on the urban model reveal the same pattern (see Figure 6 in the annex). These results have obvious desirable welfare implications. They hint at how targeting benefits will be distributed in the population. They are also consistent with Coady and Parker (2009) who found that administrative selection based on proxy-means testing is particularly effective at reducing overall program coverage while maintaining high coverage of the lowest welfare households.

4. Conclusions

This research suggests a simple and low cost method for targeting the poor and smallholder farmers in Malawi. The paper applies the logit regression (weighted) in a stepwise procedure along with out-of-sample validation and robustness tests to develop proxy means test models for the country.

The main conclusion that emerges from the results is that measures of absolute poverty estimated with logit regression can yield reasonably accurate and robust out-of-sample predictions of absolute poverty in a nationally representative sample. Furthermore, calibrating the model to a higher poverty line improves its targeting performances, while calibrating the model to a lower line does the opposite. The models also perform well in terms of those who are mistargeted; covering most of the poorest deciles and excluding most of the richest ones.

One major feature of the models developed is that household score can be easily and quickly computed. The best indicators selected are objective and easily verifiable. They are all categorical variables on which it would relatively easy and quick to collect reliable information. However, an effective verification process (e.g. home visits, triangulation, etc.) may be needed in order to limit misreports and corruption in the screening process.

The models developed in this paper can be used in a wide range of applications, including identifying and targeting the poor in Malawi. Moreover, they can be used to produce estimates of poverty rates and monitor change in poverty over time as the country and donors cannot afford the costs of frequent household expenditure surveys. Likewise, they can be used to assess household eligibility to welfare programs and the impacts of development policies targeted to those living below the poverty line. Finally, they can be used to assess the poverty outreach of microfinance institutions. Overall, the models developed can be potential policy tools for Malawi.

Though the models have proven their validity in an independent 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

Table 7. Performances of a unique national model by area

Targeting ratios / Models	Cut-off	Poverty accuracy (%)	Under coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
National model	14	73.03	26.96	24.63	-1.01	70.71
Rural area	14	73.98	26.02	24.40	-0.76	72.35
Urban area	14	57.89	42.11	28.42	-2.71	44.21
Accuracy lost						
National to rural area	14	-0.95	0.94	0.23	-0.25	-1.64
National to urban area	14	15.14	-15.15	-3.79	1.70	26.50

Source: Own computations based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

Table 8. Lost in model's accuracy after transformation (rural model)

Targeting ratios / Poverty lines	Cut-off	Poverty accuracy (%)	Under coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
National line						
original model	0.51	72.19	27.81	25.74	-0.98	70.13
transformed model	37	68.52	31.48	28.0	-1.64	65.03
International line						
original model	0.56	82.1	17.9	16.09	-1.19	80.29
transformed model	40	84.52	15.48	18.87	2.23	81.13
Extreme line						
original model	0.39	51.15	48.85	38.26	-2.38	40.57
transformed model	18	46.13	53.87	38.13	-3.54	30.39

Source: Own computations based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

Table 9. Lost in model's accuracy after transformation (urban model)

Targeting ratios / Poverty lines	Cut-off	Poverty accuracy (%)	Under coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
National line						
original model	0.37	62.16	37.84	33.33	-1.04	57.66
transformed model	20	63.96	36.04	36.94	0.21	63.06
International line						
original model	0.45	74.57	25.43	25.43	0	74.57
transformed model	22	76.30	23.70	27.17	1.25	72.83
Extreme line						
original model	0.36	47.06	52.94	52.94	0	47.06
transformed model	8	64.71	35.29	94.12	4.17	5.88

Source: Own computations based on Malawi IHS2 data. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

Table 10. Results of the maximum likelihood estimates (rural model)

Likelihood ratio: 950419.735***		Wald Chi-square: 554730.601***			
Score: 781671.495***	c-statistic = 0.837	Number of observations = 6560			
Parameter	Estimate	Standard Error	Wald 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	0.00381	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	0.00473	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	0.00345	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)					
Household grew no tobacco in the past five years	-0.2158	0.00221	9503.7619	<.0001	0.806
Household grew tobacco in the past five years (reference)					
Household head cannot read in Chichewa language	-0.1562	0.00178	7673.3451	<.0001	0.855
Household head can read in Chichewa language (reference)					

Source: Own results based on Malawi IHS2 data. *** denotes significant at the 99% level.
** denotes significant at the 95% level.

Table 11. Results of maximum likelihood estimates (urban model)

Likelihood ratio: 144809.746***			Wald Chi-square: 61435.0177***		
Score: 118028.979***	c-statistic = 0.913		Number of observations = 960		
Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Exp(Est)
Intercept	9.3575	17.4844	0.2864	0.5925	11585.87
Household lives in Mzuzu	0.0542	0.0164	10.9445	0.0009	1.056
Household lives in Linlongwe	0.5875	0.0113	2707.2585	<.0001	1.799
Household lives in Zomba	-0.4198	0.0172	595.8924	<.0001	0.657
Household lives in Blantyre (reference)					
House construction material is permanent	0.2727	0.0113	578.2221	<.0001	1.314
House construction material is semi-permanent	0.2183	0.00801	742.0303	<.0001	1.244
House construction material is traditional (reference)					
Household size is two or less	3.3718	0.0229	21627.4476	<.0001	29.132
Household size is three	1.1108	0.0146	5766.4666	<.0001	3.037
Household size is four	0.2675	0.0137	379.3309	<.0001	1.307
Household size is five	-0.9742	0.0126	6013.6759	<.0001	0.377
Household size is six or seven	-1.6360	0.0142	13220.8533	<.0001	0.195
Household size is eight or more (reference)					
Household head sleeps on bed and mattress	0.9591	0.0132	5313.1745	<.0001	2.609
Household head sleeps on bed and mat (grass on the floor)	0.7243	0.0182	1588.1906	<.0001	2.063
Household head sleeps on bed alone	-0.6038	0.0273	488.9628	<.0001	0.547
Household head sleeps on mattress alone	-0.3907	0.0170	526.0643	<.0001	0.677
Household head sleeps on mat (grass on the floor)/cloth/sack/floor (reference)					
Maximum class level attended my members is primary/nursery	-7.3580	17.4844	0.1771	0.6739	0.001
Maximum class level attended my members is secondary	-6.3898	17.4844	0.1336	0.7148	0.002
Maximum class level attended my members is training/college	7.2666	38.7130	0.0352	0.8511	431.675
Maximum class level attended my members is university (reference)					
House flooring material is sand/smooth mud/wood	-0.2782	0.00782	1266.2785	<.0001	0.757
House flooring material is smooth cement/tile (reference)					
Household owns no cellular phone in working condition	-0.8516	0.0235	1311.7994	<.0001	0.427
Household owns a cellular phone in working condition (reference)					
Toilet facility is flush toilet/VIP latrine	0.8799	0.0199	1958.8300	<.0001	2.411
Toilet facility is traditional with/without roof	-0.0248	0.0143	2.9901	0.0838	0.976
Household has no toilet facility (reference)					
Number of males in the household is zero	-0.4900	0.0253	376.1012	<.0001	0.613
Number of males in the household is one or two	0.0715	0.0117	37.4412	<.0001	1.074
Number of males in the household is three	0.3179	0.0134	561.2314	<.0001	1.374
Number of males in the household is four or more (reference)					
Household owns no paraffin or kerosene stove	-0.6537	0.0169	1504.1453	<.0001	0.520
Household owns a paraffin or kerosene stove (reference)					
Household owns no clock	-0.2652	0.00701	1433.7344	<.0001	0.767
Household owns a clock (reference)					

Source: Own results based on Malawi IHS2 data. *** denotes significant at the 99% level.
** denotes significant at the 95% level.

Table 12. Malawi rural poverty model calibrated to the national poverty line

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

Source: Own results based on Malawi IHS2 data.

Table 13. Malawi urban poverty model calibrated to the national poverty line

Indicators	Values	Weight	Score
1. Where does the household live?	Zomba	0	
	Blantyre	1	
	Mzuzu	2	
	Lilongwe	3	
2. How many people live in the household?	Eight or more	0	
	Six or seven	2	
	Five	4	
	Four	8	
	Three	11	
	Two or less	18	
3. What does the household head sleep on?	Bed alone/Mat (grass on the floor)/ clock/sack on the floor	0	
	Mattress on floor	1	
	Bed & Mat/Bed & Mattress	5	
4. What is the house type of construction material?	Traditional	0	
	Semi-permanent	2	
	Permanent	3	
5. What is the maximum class level attended by household members?	Nursery/Primary	0	
	Secondary	3	
	University	46	
	Training	48	
6. How many males live in the household?	Zero	0	
	One or two	2	
	Three	3	
	Four or more	2	
7. What is the house flooring material made of?	Sand/smooth mud/wood	0	
	Smooth cement/tile	2	
8. Is there a cellular phone in a working condition in the house?	No	0	
	Yes	6	
9. What is the type of toilet facility used by household members?	None	0	
	Traditional with/without roof	3	
	Flush toilet/VIP latrine	6	
10. Does the household own a paraffin or kerosene stove?	No	0	
	Yes	4	
11. Does the household own a clock?	No	0	
	Yes	2	
Household is deemed poor if its total score is less than 20		Total score	
	Household poverty status: Poor ☐ Non-poor ☐		

Source: Own results based on Malawi IHS2 data.

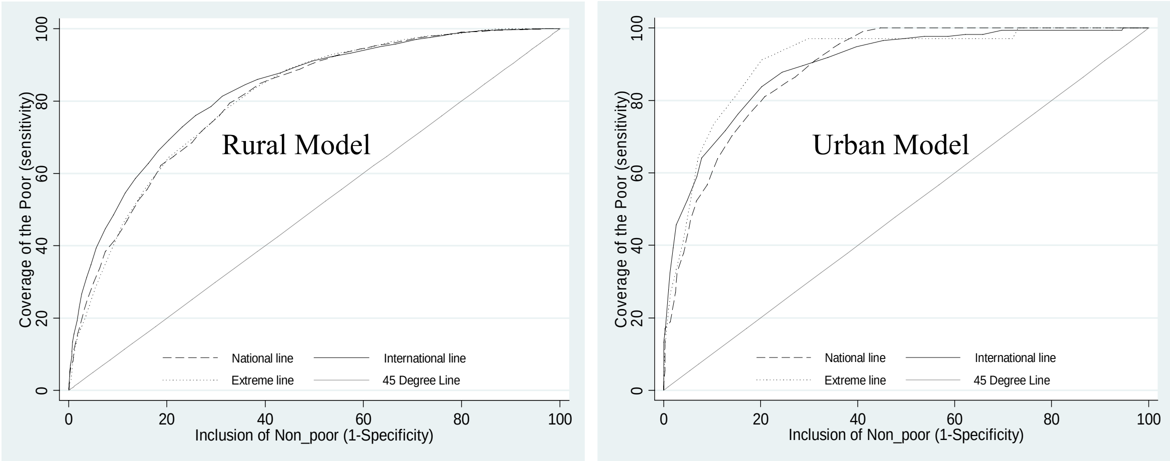

Figure 5: ROC curves of the rural model (left) and urban model (right) by poverty line.
Source: Own results based on Malawi IHS2 data.

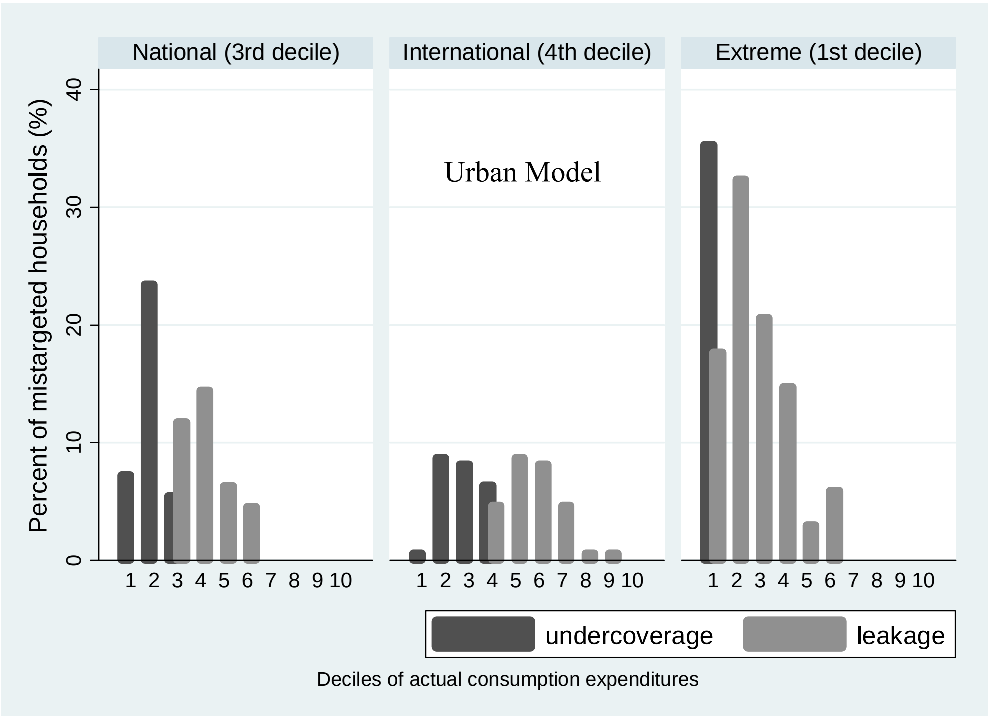

Figure 6: Distribution of targeting errors by consumption decile and poverty line.
Source: Own results based on Malawi IHS2 data.

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