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**Operational Models for Improving the Targeting Efficiency
of Agricultural and Development Policies**

A systematic comparison of different estimation methods using out-of-sample tests

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Abstract

Accurate targeting is key for the success of any development policy. While a number of factors might explain low targeting efficiency such as governance failure, political interference or lack of political will, this paper focuses on improving indicator-based models that identify poor households and smallholder farmers more accurately.

Using stepwise regressions along with out-of-sample validation tests and receiver operating characteristic curves, this paper develops proxy means tests models for rural and urban Malawi. The models developed have proved their validity in an independent sample and therefore, can be used to target a wide range of development policies at the poor. This makes the models a potentially interesting policy tool for the country.

JEL classification: *C01, C13, C51, C52, I3, I32, Q14*

Keywords – *Malawi, poverty targeting, predictions, proxy means tests, out-of-sample tests, ROC curve, bootstrap.*

1. Introduction

Malawi is a very poor and mostly agricultural country. According to the Second Integrated Household Survey (IHS2), 52.4% of the Malawians are poor and about 90% of the population live in rural areas (National Statistics Office, 2005). Likewise, most of the rural population depends on agriculture for their livelihoods.

In response to the widespread poverty and endemic food insecurity in the country, the Government of Malawi enacted different programs such as credit, fertilizer, improved seed, and conditional cash transfer through community-based and self-targeting mechanisms in order to improve the country's supply of food production and reduce poverty. However, most of these programs were not efficiently targeted at the poor and smallholder farmers. Existing statistics indicate that the problem of food insecurity remains rampant (Chinsinga, 2005). Almost all social protection programs are poorly targeted in the country.

As a result, poverty and food insecurity have not been reduced in the country. Recent estimates suggest that the poverty rate has declined by less than 2% over a decade (Government of Malawi and World Bank, 2007). It has therefore appeared that much more needs to be done to develop a low cost, fairly accurate, and easy system to target the poorest (PMS, 2000). Such an operational system is also useful for assessing whether a project, policy or development institution reaches the poor and smallholder farmers.

This paper addresses these challenges. We develop proxy means tests models for targeting poor and smallholder farmers in Malawi. Proxy means tests use household socioeconomic indicators to proxy household poverty or welfare level. Proxy means tests have the merit of making replicable judgments using consistent and visible criteria (Coady et al., 2002). They are also simple to implement and less costly than sophisticated means tests¹.

¹ See Coady et al. (2002) and Grosh and Baker (1995) for further details on means tests.

In addition to the Weighted Least Square (WLS) estimation method, we apply the Weighted Logit regression with a stepwise selection routine to select the best set of indicators for correctly predicting the household's poverty status. Furthermore, we compare the predictive power and the robustness of both estimation methods using out-of-sample tests and Receiver Operating Characteristic (ROC) curves. Finally, we estimate the prediction intervals of the model's performance measures using the bootstrap algorithm.

The set of indicators used in our models include objective and easily verifiable variables. These variables are usually available in Living Standard Measurement Surveys (LSMS) data and most household surveys in developing countries.

This paper is organized as follows. Section 2 sets out the methodology, whereas section 3 presents the results with applications to household data from Malawi. Section 4 ends the work with concluding remarks.

2. Data and Methodology

2.1 Data

This research uses the Second Malawi Integrated Household Survey (IHS2) data. The National Statistics Office (NSO, 2005) of Malawi conducted the IHS2 with the assistance of IFPRI and the World Bank². The IHS2 was carried out from March 2004 through March 2005 and covered a nationally representative sample of 11,280 households that were selected based on a two-stage stratified sampling design. This design involved in the first stage the selection of the Primary Sampling Units (PSU) based on Probability Proportional to Size sampling (PPS) and in the second stage, a random selection of 20 households per PSU.

Compared to previous experiences, this survey is particularly appropriate for the research for three reasons. First, it used an improved methodology for collecting and

² We gratefully acknowledge the National Statistics Office of Malawi (NSO) for providing us with the data.

computing household consumption expenditures. Second, the survey covered a wide range of poverty indicators that are potentially suitable to developing proxy means tests models. Third, 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, but nonetheless narrow view of poverty (Benson, 2002). It excludes several important components of personal and household well-being, including physical security, level of participation in networks of support and affection, access to important public social infrastructure such as health and educational services, and whether or not one can exercise ones human rights. In sum, there is more to assessing the quality of life and the welfare of individuals than consumption and expenditure. In view of the widespread use of monetary poverty lines with expenditure-based measures of poverty however, 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.

2.2 Model's Estimation Methods

2.2.1 Poverty Predictors and Sample Selection

The set of poverty predictors includes 148 practical indicators that were selected to ensure an operational use of the tools³. The practicality refers to two criteria: *difficulty and verifiability of indicators*. Initially, variables that are difficult to measure, verify (for example, subjective variables) and compute were excluded from the set of available variables. Before estimating the regressions, the list of selected variables was further screened for

³ The list of indicators was reduced to 112 for the urban model; some of the variables were not relevant in urban area.

multicollinearity within dimension⁴. This screening of potential poverty predictors is the first step towards the selection of indicators that are significantly associated with poverty.

Separate models were estimated for rural and urban households for two main reasons. First, the Malawi poverty report revealed different profiles for urban and rural households. Second, the interactions between the regions and other variables were found to be statistically significant in a national-level model.

In order to perform the validation tests, each sample was first split into two sub-samples following 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 therefore applied the set of identified indicators and their derived weights to predict the household's 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 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. 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

⁴ All variables with a bivariate correlation coefficient of more than 0.65 or a variance inflation factor of more than 10 were removed from the sets.

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
<i>Number of indicators</i>	148	112	-

Source: Own calculations based on Malawi IHS2 data

2.2.2 Estimation Methods

Two estimation methods were applied. These included: the Weighted Least Square method (WLS) and the Weighted Logit (WL) regressions. As stated earlier, both regressions were weighted in order to account for the importance of each household in the total population. A weighted regression is also appropriate in the presence of heteroscedasticity⁵. Both regression methods are widely used in the literature. However, there is a debate on the merits of welfare regressions versus binary poverty models. The Weighted Least Square⁶ uses the full information available by estimating the model over the entire welfare spectrum, whereas the Weighted Logit collapses the entire expenditure distribution into two values. In their poverty regressions, Braithwaite et al. (2000) justify the use of the logit by the possibility of systematic measurement errors in the dependent variable. These authors also add that it is a judgment call whether the loss of information embodied in the binary regression outweighs the risk of bias due to measurement error. In this paper, we systematically compare the targeting performances of both methods to derive the best for targeting poor households and improving the efficiency of agricultural development policies.

⁵ One of the critical assumptions of ordinary least square regression is homoscedasticity. When this assumption is violated, WLS compensates for violation of the homoscedasticity assumption by weighting cases differentially. Cases with greater weight contribute more to the fit of the regression. The result is that the estimated coefficients under the WLS have smaller standard errors.

⁶ For example Grosh and Baker (1995) argue that strictly speaking, ordinary least square is not appropriate for predicting poverty. Glewwe (1992) and Ravallion and Chao (1989) try to solve the problem of targeting using more complex poverty minimization algorithms. These methods are however difficult to implement and have limited applications compared to the methods used in this paper.

Both methods sought to identify the best set of ten indicators for predicting the household's poverty status. Previous researches show that in general, the higher the number of indicators, the higher the achieved accuracy (Zeller and Alcaraz, 2005; Zeller *et al.*, 2005). Higher accuracy is often achieved at a cost of practicality, but also entails a higher cost of data collection. Therefore, we limit the number of indicators to the best ten in order to balance the cost of data collection, practicality, and operational use of the models. Furthermore, most analysts favor the use of ten regressors in an operational poverty targeting model.

A model with a high explanatory power is a prerequisite for good predictions of the dependent variable per-capita daily expenditures (and thereby poverty status). Therefore, for the WLS, the best ten regressors were selected based on the Stepwise-MAXR routine of SAS (SAS Institute, 2003) that maximizes the model's explained variance (R-square). For the WL, the best ten regressors were selected using the stepwise score routine of SAS. Similarly to the MAXR routine, SAS offers a stepwise score routine for best subset selection of variables with logistic regressions. The stepwise-score uses the branch and bound algorithm of Furnival and Wilson (1974) to find a specified number of models with the highest likelihood score (chi-square) statistic (SAS Institute, 2003). In other words, the stepwise-score seeks the best set of variables that maximizes the likelihood score (chi-square) statistic.

The WLS used the continuous dependent variable logarithm of daily per capita expenditures⁷, whereas the WL had as dependent variable a dummy variable that is coded one if the household is poor (expenditures below the national poverty line) and zero otherwise. In other words, the WL model estimates the probability of a household being below the poverty line.

In the rural model, we controlled for agricultural development districts 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

⁷ The logarithm of expenditures was used instead of simple expenditures because the log function better approximates a normal distribution.

unobservable factors in the model. Likewise, we controlled for the four major cities: Mzuzu, Zomba, Lilongwe, and Blantyre in the urban model.

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). But 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, the above models do 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.

2.2.3 Predicting the household's poverty status

Having estimated the model, the question arises as to what cut-off to use to predict the household's poverty status. We therefore, explored three classifications based on three different cut-offs: *national*, *percentile-corrected*, and *maximum-BPAC* cut-offs.

In the first classification, the most obvious one, the predicted per capita expenditures from the WLS were compared to the *national poverty line* to derive the *predicted household's poverty status*. Households with less than 44.29MK daily per capita expenditures were classified as *poor* and those with higher daily per capita expenditures were deemed *non-poor*. This poverty line matches the actual poverty rate in the total population. Similarly, the probability of being poor estimated with the WL regression was compared to the cut-off point (predicted probability) that matches the actual poverty rate in the population. Household with

higher probability than this cut-off point were predicted as *poor*, otherwise they were deemed *non-poor*.

However, the above classification ignores the unknown error in the estimation of household expenditures. As a result, it would give biased estimates of poverty rates (Hentschel et al., 2000) and thereby accuracy performances. Therefore, a second classification based on the *percentile-corrected poverty line* (PC) was used⁸. Figure 1 illustrates the national and percentile-corrected poverty lines from the WLS method. As shown in the graph, the PC poverty line is the line that matches the actual poverty rate in the distribution of predicted expenditures from the model estimation. Both poverty lines on the graph differ, but the difference between them is small since the vertical lines are very close to each other.

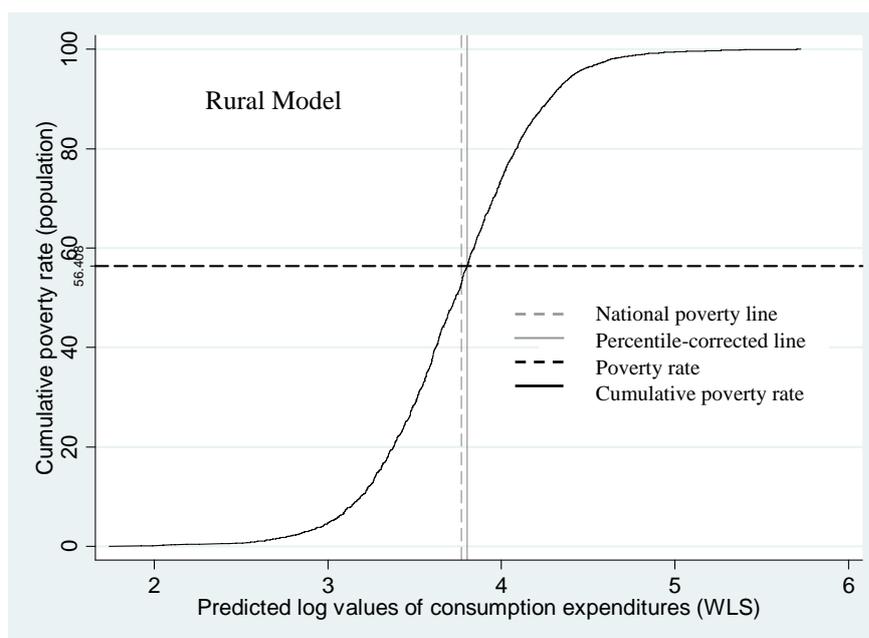


Figure 1 Cumulative distribution of poverty rate
Source: Own results based on Malawi IHS2 data

The third classification approach used to predict the household's poverty status applies cut-off that maximizes the *Balanced Poverty Accuracy Criterion* (BPAC)⁹ which is the

⁸ See Johannsen (2007) for further details on the percentile-corrected approach.

⁹ See section 2.3 for further details on BPAC.

estimation method's overall performance measure. Table 2 summarizes the decision rule for predicting the household's poverty status.

Table 2. Decision rule for predicting the household's poverty status

Method Classification type	Weighted Least Square	Weighted Logit
<i>Cut-off 1</i>	Poverty line	Probability that matches poverty line
<i>Cut-off 2</i>	Percentile-corrected line (PC)	Probability that matches PC line
<i>Cut-off 3</i>	Poverty line that maximizes BPAC*	Probability that maximizes BPAC

Source: Own presentation. See section 2.3 for details on BPAC

The three poverty classifications in Table 2 were then crossed with the *actual household's poverty status*. The latter was determined by comparing the actual daily per capita expenditures to the national poverty line as in the first classification above. The two-by-two cross-table of the actual and predicted poverty statuses was subsequently used to describe the outcomes of the predictions as exemplified in Table 3.

Table 3. Net benefit matrix of poverty classification (hypothetical figures)

Actual poverty status	Predicted poverty status		Total
	Non-poor	Poor	
Non-poor	20	15	35
Poor	10	5	15
Total	30	20	50

Source: Own presentation

Table 3 suggests that 5 out of 15 actually poor households were correctly predicted as poor, whereas the remaining 10 households were wrongly predicted as non-poor. Likewise, 20 out of 35 actually non-poor households, were correctly predicted as non-poor, while the remaining 15 households were wrongly predicted as poor. The above example suggests that the net benefit matrix yields correct as well as incorrect predictions of the household's poverty status. Based on the results, different performance measures can then be calculated 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 model. This paper focuses on selected ratios which are especially relevant for poverty targeting (Table 4).

Table 4. 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 undercoverage and leakage, measured in percentage points

Source: Adapted from IRIS (2005)

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 poverty rate. Positive values of PIE indicate an underestimation of the poverty incidence, whereas negative values imply the opposite. The 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 method'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 policy maker may give higher or lower weight to undercoverage compared to leakage. This is in principle possible by altering the weight for leakage in the BPAC formula.

2.3.2 Assessing the predictive power and robustness of the models.

Out-of-sample validation tests were performed to ascertain the predictive power and the robustness of the models. The main purpose of the validation is to observe how well the models perform in an independent sample derived from the same population. A model with high predictive power 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, their weights, and cut-offs to the validation sub-samples in order to predict the household's 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's 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 2 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.

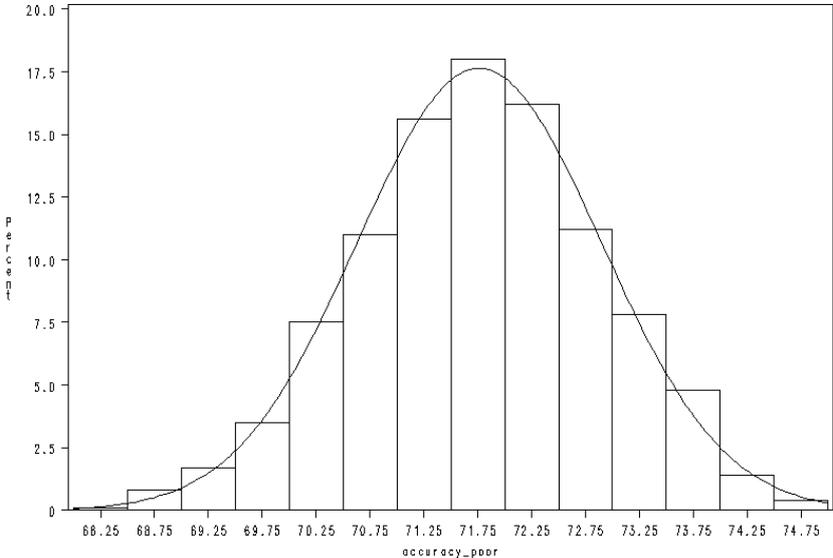


Figure 2: Bootstrapped distribution of the poverty accuracy (WLS)
Source: Own results based on Malawi IHS2 data.

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. Results and Discussions

This section discusses the out-of-sample results of the models¹⁰. First, we briefly describe the poverty lines applied. Then, the targeting performances of the models differentiated by regression methods and poverty classifications are presented. The classification that yields the highest performances is selected and flagged with the prediction intervals. We then compare the aggregate accuracy of both estimation methods out-of-sample. Finally, we analyze the sensitivity of the models to the poverty line and the distribution of the targeting errors.

3.1 Modelling the household's poverty status: Empirical results

Table 5 gives an overview of the poverty lines and rates in Malawi. The full regression results, including the indicator lists are presented in Tables 9 thru 12 in the annex. All of the coefficient estimates of the best indicator sets are statistically significant and their signs are consistent with expectations and economic theory.

Table 5. Malawi poverty rates by region and poverty line (as of 2005)¹¹

Type 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 computations based on Malawi IHS2 data, Chen and Ravallion (2008), and the World Bank (2008). MK denotes Malawi Kwacha, national currency. PPP stands for Purchasing Power Parity.

As shown in Table 5, the poverty rate in Malawi is estimated at 52.4% under the national poverty line of 44.29MK. This rate suggests that 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

¹⁰ For brevity reasons, only out-of-sample results are presented throughout the paper. The results from the model's calibration are available upon request.

¹¹ These rates differ slightly from the official statistics because of errors in the weights of the IHS2 report.

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 is set at MK29.31. Under the extreme poverty line, 26% of the Malawian population are very poor. These poverty rates are lower when expressed in percent of households. Table 6 presents the rural model's results by classification type.

Table 6. Rural model's predictive accuracy by classification type

	Targeting ratios Method Cut-off	Cut-off value (MK)	Poverty accuracy (%)	Under- coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
WLS	<i>National</i>	3.79	64.07	35.94	20.45	-7.32	48.58
	<i>Percentile</i>	3.80	65.43	34.58	21.74	-6.07	52.58
	<i>Max BPAC</i>	3.85	72	28	26.32	-0.79	70.32
WL	<i>National</i>	0.59	58.77	41.23	16.58	-11.65	34.13
	<i>Percentile</i>	0.66	48.85	51.16	11.42	-18.78	9.10
	<i>MaxBPAC</i>	0.48	71.61	28.39	27.10	-0.61	70.32

Source: Own computations based on Malawi IHS2 data.

Table 6 suggests that for the WLS method, the cut-off that maximizes the BPAC in-sample (*MaxBPAC*) yields the highest out-of-sample performances, followed by the percentile-corrected poverty line, and then the national poverty line. The first is however, associated with the highest leakage. The same trend applies to the WL method; except that the percentile-corrected poverty line yields the lowest performances in that case. The results show that the classification by the *MaxBpac* cut-off consistently yields the highest BPAC out-of-sample.

These results also illustrate the trade-off between undercoverage and leakage ratios as increasing the cut-off¹² reduces the undercoverage (improves the poverty accuracy), but also results in higher leakage to the non-poor. The performances of the urban model (see Table 13

¹² This trade-off also applies to the WL method, but when reducing the cut-off, because the method estimates the probability of being poor.

in the annex) follow the same pattern as the rural model. Therefore, the cut-off that maximizes the BPAC in the calibration sample was selected as the one that yields the best classification of the household's poverty status out-of-sample. Table 7 describes the results of the rural and urban models at these optimal cut-offs, including their prediction intervals.

Table 7. Model's predictive accuracy at optimal cut-offs

Model	Targeting ratios Method	Cut-off value (MK)	Poverty accuracy (%)	Under- coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
<i>Rural</i>	<i>WLS</i>	3.85	72 (69.7; 74.2)	28 (25.8; 30.3)	26.32 (23.4; 29.1)	-0.79 (-2.4; 0.96)	70.32 (64.9; 73.5)
	<i>WL</i>	0.48	71.61 (69.6; 74.0)	28.39 (26.0; 30.4)	27.10 (24.2; 30.0)	-0.61 (-2.33; 1.13)	70.32 (65.2; 73.2)
<i>Urban</i>	<i>WLS</i>	3.92	62.16 (53.3; 71.0)	37.84 (29.0; 46.7)	38.74 (26.3; 52.8)	0.21 (-3.54; 3.75)	61.26 (40.9; 66.5)
	<i>WL</i>	0.39	61.26 (51.7; 70.5)	38.74 (29.5; 48.3)	39.64 (27.3; 53.5)	0.21 (-3.23; 3.96)	60.36 (40.9; 66.0)

Source: Own computations based on Malawi IHS2 data. Bootstrapped prediction intervals in brackets

Table 7 shows that the WLS method yields a poverty accuracy of 72% and a BPAC of 70.32% points for the rural model. This result indicates that the model would cover about 72% of the poor households - that is about seven out of every ten poor households - when applied to target poverty in Malawi. The undercoverage is estimated at 28%, while the leakage is set at 26.32% for the same model and estimation method. The PIE nears 0% points, which implies that the method perfectly predicts the poverty rate out-of-sample. Likewise, the WL method yields a poverty accuracy of about 72% and a BPAC of 70.32% points for the rural model. In addition, the estimated PIE is close to 0% points, whereas undercoverage and leakage are estimated at 28.39% and 27.10%, respectively. These results show that the WLS and the WL yield the same BPAC and PIE, but the former slightly outperforms the latter in terms of poverty accuracy and leakage. Using the BPAC to assess the estimation method's overall accuracy, the results of the rural model show that both methods perform equally. Even when considering single accuracy measures such as poverty accuracy or leakage, both methods do not differ much in terms of targeting performances.

As concerns the urban model, Table 7 indicates that the WLS and WL methods yield the same PIE of 0.21% points which indicate that they both predict the poverty rate remarkably well. However, the former yields a slightly higher BPAC (61.26%) and poverty accuracy (62.16%) compared to the latter. Besides, its leakage is lower (38.74%). Though the WLS method slightly outperforms the WL method, the results of the urban model also show that the differences in performances are not much between both methods. Nonetheless, the leakage and undercoverage are deceptively high in both cases.

The relatively low performance of the urban model as compared to the rural model is partly driven by the level of actual poverty rate in the urban area: 20% versus 47%. Therefore, the lower the poverty rate, the weaker the model's performance. 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 household consumption expenditures point to this argument. Nevertheless, even though undercoverage and leakage are high in urban area, these errors amount to relatively small number of poor; less than 15% of the Malawian population live in urban area.

As concerns the prediction intervals, Table 7 shows that the interval lengths are very short for the rural model with a maximum width of 8% points, indicating a very robust model. Conversely, the results of the urban model suggest a less robust tool with higher interval lengths. These results are explained by the lower size of the validation sample of the urban model as shown in Table 1.

As a whole, the above findings suggest that both estimation methods perform equally, with the WLS slightly outperforming the WL¹³. Likewise, the rural model performs better than the urban model which is less robust. Section 2.3 compares the estimation method's aggregate performances.

¹³ To allow for a stricter comparison of both estimation methods, we used in separate simulations the same indicator set to fit both regressions. The results however do not differ from the observed performances.

3.2 Estimation method's aggregate performances

To compare the aggregate predictive power of the WLS and WL regressions, the Receiver Operating Characteristic (ROC) curves were plotted based on the predictions of the validation sample. Unlike the results in section 3.1 which were based on one single cut-off – the cut-off that maximizes the BPAC in-sample –, the ROC curve shows the trade-off between the coverage of the poor or poverty accuracy and the inclusion of non-poor or inclusion error¹⁴ at different cut-offs across the predicted welfare (WLS) or probability (WL) spectrum. Earlier applications of ROC curves for poverty assessment include Wodon (1997), Baulch (2002), and Schreiner (2006) who applied the curve in combination with logistic regression in a calibration sample only. However, apart from Johannsen (2007), no research has to our knowledge applied the ROC curve out-of sample to assess the accuracy performances of different estimation methods.

Figure 3 displays the ROC curves of the rural model. In addition, Figure 4 illustrates the BPAC distributions across the cut-off spectrum.

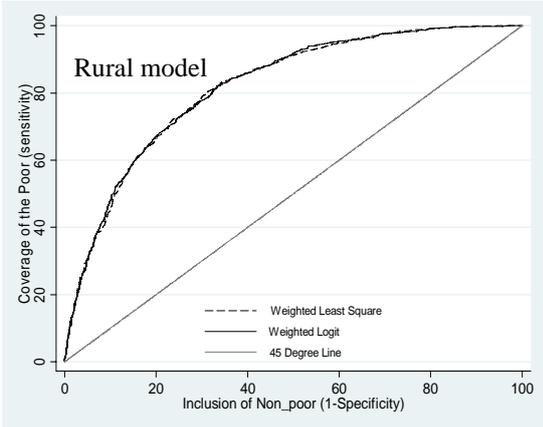


Figure 3: ROC curves of the rural model
Source: Own results based on Malawi IHS2 data

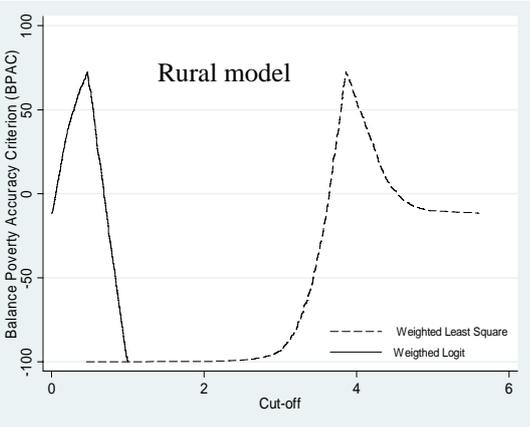


Figure 4: BPAC curves of the rural model
Source: Own results based on Malawi IHS2 data

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 predicting 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. See Wodon (1997) and Baulch (2002) for further details on ROC curves.

Figure 3 shows that the higher the coverage of the poor, the higher the inclusion of non-poor. For example, 80% coverage of the poor would lead to an inclusion of about 30% of the non-poor households. Increasing the coverage of the poor to 90% would lead to more than 40% of the non-poor households being wrongly targeted. The curves follow a similar pattern with minor exceptions. While both curves are monotonically increasing, their shape depends on the performances underlying each model used to predict the poverty status of the households. Both curves cover up in the lower (below 40% sensitivity level), middle (between 50% and 65%; between 85% and 90%), and extreme upper (above 95%) sections of the graph. This pattern illustrates that they achieve the same coverage of the poor in these sections of the graph. Between 40% and 50% sensitivity level, the WL yields slightly higher accuracy, whereas the WLS performs better between 65% and 70% sensitivity level. These results suggest that none of the estimation methods consistently yields the highest coverage of the poor across the ROC curves. In the relevant band of sensitivity (from 70% to 90%) however, both methods perform equally.

Furthermore, by visual inspection, the areas under the curves are not much different. To confirm this statement, we tested the difference between the coverage of the poor of both curves. The results of the tests show that there is no statistically significant difference between both distributions. Therefore, both estimation methods yield approximately the same level of aggregate predictive accuracy. This result is consistent with the findings in Table 7 which suggest that both methods do not differ much in terms of achieved targeting performances. More to this point, the accompanying BPAC curves (Figure 4) show that the maxima obtained out-of-sample (about 73% points) are not much different from the performances presented in Table 7. The reason behind is that the cut-offs applied to the validation sample are closer to the out-of-sample optima. This indicates that the cut-offs that maximize the BPAC in the

calibration sample converge towards the out-of-sample optima¹⁵. The same trend applies to the urban model (Figures 5 and 6).

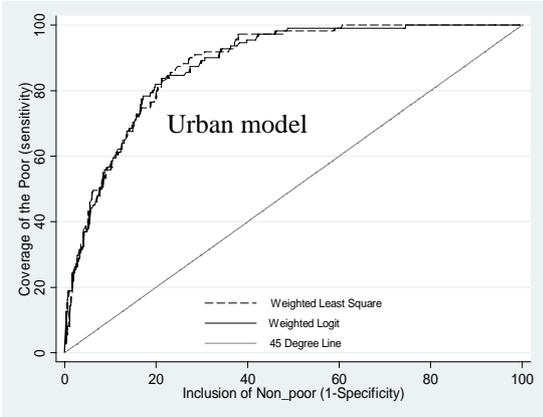


Figure 5: ROC curves of the urban model
Source: Own results based on Malawi IHS2 data

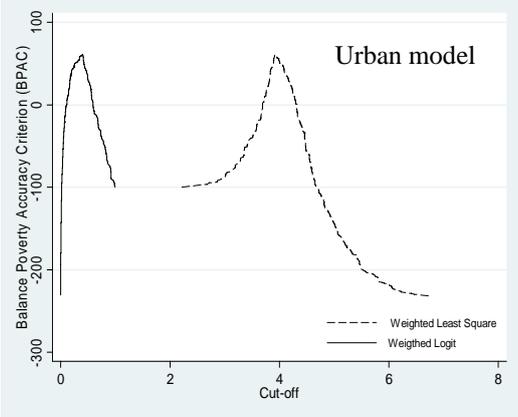


Figure 6: BPAC curves of the urban model
Source: Own results based on Malawi IHS2 data

Figure 5 indicates that in the relevant band of sensitivity (from 70% to 90%), the WL outperforms the WLS within the lower section of the band, whereas the WLS outperforms the WL in the upper section of the band. Likewise, the difference between the distributions of both curves is found to be statistically not significant. Therefore, both methods do not differ in terms of aggregate predictive accuracy. This result is consistent with the findings in Table 7.

As stated earlier, the cut-off that maximizes the BPAC in the calibration sample is used to judge the method’s overall targeting performance out-of-sample. However, a policy maker may set a different cut-off using the ROC curve to decide on the number of poor a program or project should reach and ponder on the number of non-poor that would be incorrectly targeted. The best indicators selected are objective and easily verifiable (see regression results in the annex). Information on these indicators can be quickly collected at low cost by a survey agent to determine the household’s poverty status.

¹⁵ A similar trend emerges when the models were calibrated to the international and extreme poverty lines.

3.3 How do the model's results change with 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 5. For the WLS method, the list of the best indicators selected is the same across poverty lines. However, since the dependent variable in the WL method - the household's 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 8 shows the results of the simulations.

Table 8. Model's sensitivity to poverty line

Method	Targeting ratios Poverty line*	Cut-off	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
<i>Rural Model</i>							
WLS	<i>International</i>	4.03	82.33 (80.9; 83.9)	17.67 (16.1; 19.1)	16.60 (14.7; 18.4)	-0.70 (-2.26; 0.96)	81.27 (77.7; 83.3)
	<i>Extreme</i>	3.56	49.93 (46.4; 53.4)	50.07 (46.6; 53.6)	39.21 (34.2; 44.4)	-2.44 (-3.87; -0.98)	39.08 (30.9; 48.1)
WL	<i>International</i>	0.56	82.61 (81.1; 84.2)	17.39 (15.8; 18.9)	16.18 (14.4; 18.1)	-0.79 (-2.22; 0.87)	81.40 (77.9; 83.6)
	<i>Extreme</i>	0.36	53.05 (49.6; 56.7)	46.95 (43.3; 50.4)	38.54 (33.5; 44.1)	-1.89 (-3.37; -0.35)	44.64 (35.9; 53.7)
<i>Urban Model</i>							
WLS	<i>International</i>	4.18	74.57 (68.3; 81.2)	25.43 (18.8; 37.1)	24.86 (17.4; 34.2)	-0.21 (-3.75; 3.65)	73.99 (59.5; 77.6)
	<i>Extreme</i>	3.52	50 (31.8; 67.7)	50 (32.3; 68.2)	73.53 (43.7; 123.0)	1.67 (-0.83; 4.17)	26.47 (-23.4; 50.5)
WL	<i>International</i>	0.43	73.99 (67.7; 79.9)	26.01 (20.1; 32.3)	26.59 (18.6; 36.2)	0.21 (-3.75; 3.96)	73.41 (59.5; 76.6)
	<i>Extreme</i>	0.30	47.06 (31.0; 64.7)	52.94 (35.3; 69.0)	61.77 (32.1; 104.4)	0.63 (-1.88; 3.13)	38.23 (-5.61; 51.7)

Source: Own results based on Malawi IHS2 data. WLS= Weighted Least Square WL= Weighted Logit Prediction intervals in brackets. *See Table 5 for description of poverty lines.

Table 8 shows that raising the poverty line to US \$1.25 (MK59.175 PPP) increases the BPAC and the coverage of the poor by about 10% to 14% points and reduces the leakage by the same margin depending on the models and estimation methods applied. These results suggest a sizable improvement in the model's targeting performances with about 82% and

74% of the poor households correctly targeted by the rural and urban models respectively. Nearly, all of the poor households are identified and covered in these scenarios.

On the other hand, reducing the poverty line to MK29.31 disappointingly reduces the targeting performances of the rural model by 10% to 30% points depending on the ratios and estimation methods. For the urban model, the reduction in targeting performances ranges from 12% to 35% points. Furthermore, both models estimate the observed poverty rate remarkably well when calibrated to the international poverty line as compared to the extreme poverty line; in that case the deviation from the observed poverty rate is much higher as shown by the PIE.

Likewise, the results show that given the model, both estimation methods do not differ much in terms of performances when calibrated to the international poverty line. On the contrary, the difference between both methods is more perceptible when calibrated to the extreme poverty line. The comparison of the ROC curves point towards the same conclusion (Figures 9 thru 12 in the annex). These results confirm the findings in Table 7 and the conclusions regarding the ROC curves in Figures 3 and 5. The following section analyzes the distribution of the targeting errors across poverty deciles.

3.4 Targeting error distribution

As we have seen in the previous sections, irrespective of the poverty line and estimation methods applied, the models yield some targeting errors, though these errors decrease with increasing poverty line. This is due to the inherent model's estimation error. While it is unsatisfactory to undercover poor or wrongly target non-poor households, 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 out-of-sample distribution of the model's undercoverage and leakage by deciles of actual consumption expenditures for the three poverty lines (Figures 7 and 8).

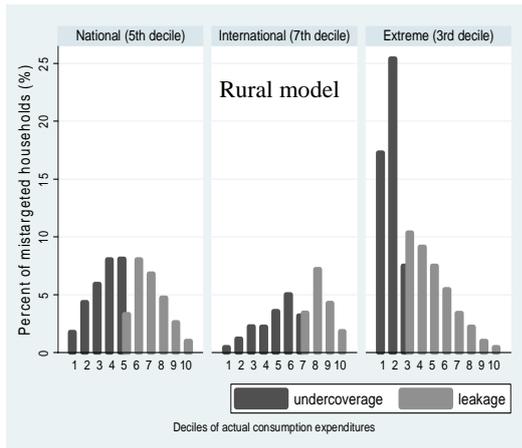


Figure 7: Targeting errors by poverty line (WLS) Source: Own results based on Malawi IHS2 data.

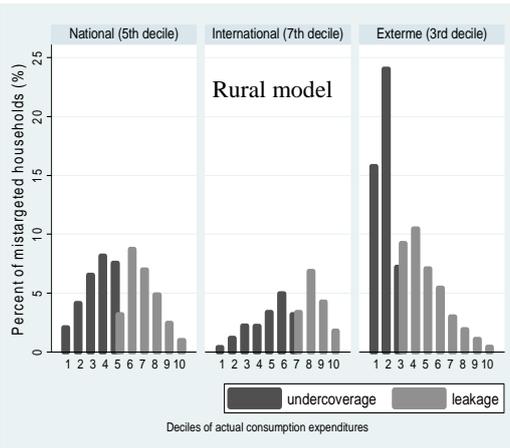


Figure 8: Targeting errors by poverty line (WL) Source: Own results based on Malawi IHS2 data.

Figure 7 shows that when the rural model is 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, and the WL estimation method (Figure 8).

These results suggest that the model performs quite well in terms of the poor households who are incorrectly excluded and the non-poor households who are wrongly targeted; covering most of the poorest deciles and excluding most of the richest ones. Further findings revealed the same pattern for the urban model (see Figures 13 and 14 in the annex). These results have obvious desirable welfare implications.

4. Concluding Remarks

This paper proposes empirical models for improving the poverty outreach of agricultural and development policies in Malawi. Furthermore, the research analyzes the out-of-sample performances of two estimation methods in targeting the poor. The developed models were calibrated to three different poverty lines as a set of policies might explicitly target different poverty groups in the population.

Findings suggest that both estimation methods achieve the same level of targeting performances out-of-sample. This is confirmed by the ROC curves which show no sizable difference in aggregate predictive accuracy between both methods. Likewise, calibrating the models to a higher poverty line improves its targeting performances, while calibrating the models to a lower line does the opposite. With regards to the targeting errors, the models perform well in terms of those who are mistargeted; covering most of the poorest deciles and excluding most of the richest ones.

The set of selected indicators are easily observable and verifiable, implying a low cost and fairly simple system to identify the poor. The models developed can be used to improve the existing targeting mechanisms of agricultural input programs in the country. Furthermore, they can be applied to target a wide range of development policies to poor households and estimate the poverty rate over time. Similarly, they can be used to assess the poverty impacts of such policies. This makes the models a potentially interesting policy tool for Malawi.

However, the observed patterns could be refined with additional validations across time as suitable data become available. Likewise, the estimations of the potential impacts of the models on poverty, its benefits, and costs are left out for further research.

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Annexes

Table 9. Weighted Least Square regression results (rural model)

		Model significance F= 329.25***		
		Adj. R ² = 0.4597	Number of observations= 6560	
	Indicator set	Parameter Estimates	Standard Errors	T-values
<i>Control variables</i>	Intercept	4.337***	0.037	115.86
	Agricultural development district is Mzuzu	0.078**	0.038	2.07
	Agricultural development district is Kasungu	0.257***	0.037	6.96
	Agricultural development district is Salima	0.164***	0.039	4.21
	Agricultural development district is Lilongwe	0.220***	0.035	6.38
	Agricultural development district is Machinga	-0.079**	0.034	-2.31
	Agricultural development district is Blantyre	-0.036	0.034	-1.04
	Agricultural development district is Ngabu	0.009	0.040	0.24
<i>Best 10 indicators</i>	1. Household size	-0.169***	0.003	-60.94
	2. Number of members who can read in English	0.082***	0.006	14.36
	3. Household has grown tobacco in past five cropping seasons	0.119***	0.016	7.63
	4. Floor of main dwelling is predominantly made of smooth cement	0.192***	0.019	10.19
	5. Number of separate rooms occupied by household excluding toilet, storeroom or garage	0.047***	0.005	9.41
	6. Cooking fuel is collected firewood	-0.152***	0.017	-9.06
	7. Bed ownership	0.161***	0.016	10.35
	8. Tape, CD player, or HiFi ownership	0.179***	0.018	9.67
	9. Electric, gaz stove or hot plate ownership	0.610***	0.067	9.16
	10. Bicycle ownership	0.154***	0.013	12.31

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

** denotes significant at the 95% level.

Table 10. Weighted Logit regression results (rural model)

		Wald=520598.859***		
		Number of observations= 6560		
		Parameter	Standard	Wald Chi-
Indicator set		Estimates	Errors	Square
Control variables	Intercept	-1.496***	0.010	22891.540
	Agricultural development district is Mzuzu	-0.478***	0.011	1972.800
	Agricultural development district is Kasungu	-1.258***	0.011	13756.947
	Agricultural development district is Salima	-0.326***	0.011	887.511
	Agricultural development district is Lilongwe	-0.973***	0.010	9748.009
	Agricultural development district is Machinga	0.293***	0.010	914.526
	Agricultural development district is Blantyre	0.031***	0.010	9.969
	Agricultural development district is Ngabu	-0.068***	0.011	35.864
Best 10 indicators	1. Household size	0.703***	0.001	421164.019
	2. Number of male adults in the household	-0.276***	0.003	11877.869
	3. Number of members who can read in English	-0.302***	0.002	29751.164
	4. Household has grown tobacco in past five cropping seasons	-0.482***	0.004	11686.453
	5. Floor of main dwelling is predominantly made of smooth cement	-0.971***	0.006	29707.046
	6. Any household members sleep under a bed net?	-0.451***	0.004	14831.047
	7. Bed ownership	-0.558***	0.004	15565.326
	8. Tape, CD player, or HiFi ownership	-0.708***	0.006	15968.654
	9. Bicycle ownership	-0.481***	0.004	17194.069
	10. Paraffin lantern ownership	-0.485***	0.004	15156.778

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

Table 11. Weighted Least Square regression results (urban model)

		Model significance F= 176.05***		
		Adj. R ² = 0.7035		
		Number of observations= 960		
Indicator set		Parameter	Standard	T-values
		Estimates	Errors	
Control variables	Intercept	4.903***	0.074	66.14
	Lilongwe city	0.061	0.063	0.97
	Zomba city	-0.351***	0.084	-4.19
	Blantyre city	-0.200***	0.063	-3.15
Best 10 indicators	1. Household size	-0.240***	0.009	-28.20
	2. Number of members who can read in English	0.073***	0.013	5.84
	3. Maximum class level ever attended in the household is superior/post secondary	0.413***	0.070	5.91
	4. Number of separate rooms occupied by household excluding toilet, storeroom, or garage	0.083***	0.016	5.07
	5. Cooking fuel is collected firewood	-0.419***	0.052	8.08
	6. Household owns a landline telephone in working condition?	0.351***	0.079	4.45
	7. Household has electricity working in the dwelling	0.316***	0.043	7.29
	8. Bed ownership	0.263***	0.038	6.87
	9. Television & VCR ownership	0.333***	0.061	5.51
	10. Electric, gas stove, or hot plate ownership	0.263***	0.060	4.38

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

Table 12. Weighted Logit regression results (urban model)

		Parameter Estimates	Standard Errors	Wald Chi-Square
Likelihood ratio= 140465.169***		Wald= 63111.546***		
Score= 123575.755***		Number of observations= 960		
Indicator set		Parameter Estimates	Standard Errors	Wald Chi-Square
<i>Control variables</i>	Intercept	-3.913***	0.036	12181.583
	Lilongwe city	0.035	0.023	2.390
	Zomba city	1.012***	0.030	1168.705
	Blantyre city	0.987***	0.024	1704.266
<i>Best 10 indicators</i>	1. Household size	0.721***	0.004	40401.758
	2. Number of members who can read in English	-0.124***	0.005	636.188
	3. Household can read in Chichewa language	-0.672***	0.015	2114.769
	4. Highest class level ever attended by females in the household is secondary/post primary	-1.466***	0.020	5294.979
	5. Dwelling construction material is traditional	0.862***	0.015	3499.259
	6. Cooking fuel is collected firewood	0.926***	0.017	2905.106
	7. Household has electricity working	-1.751***	0.025	5094.946
	8. Household head sleeps on Mat (grass) on floor	1.021***	0.0133	5903.420
	9. Television & VCR ownership	-2.108***	0.0473	1984.649
	10. Is there a place to purchase common medicines such as panadol in this community?	-0.831***	0.0202	1697.948

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

Table 13. Urban model's predictive accuracy by type of classification

	Targeting ratios	Cut-off probability	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
<i>WLS</i>	<i>National</i>	3.79	49.55	50.45	23.42	-6.25	22.52
	<i>Percentile</i>	3.85	55.86	44.14	31.53	-2.92	43.24
	<i>Max BPAC</i>	3.92	62.16	37.84	38.74	0.21	61.26
<i>WL</i>	<i>National</i>	0.32	67.57	32.43	46.85	3.33	53.15
	<i>Percentile</i>	0.01	99.1	0.90	200.15	49.58	-100.15
	<i>Max BPAC</i>	0.39	61.26	38.74	39.64	0.21	60.36

Source: Own results based on Malawi IHS2 data.

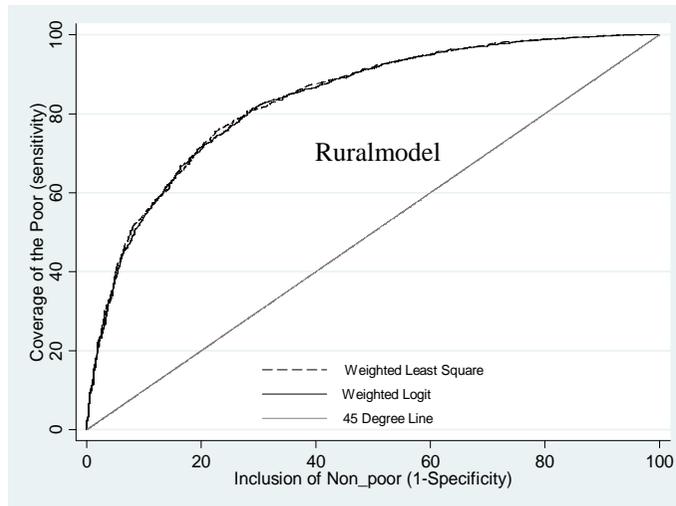


Figure 9: ROC curves of the rural model (international line)
Source: Own results based on Malawi IHS2 data.

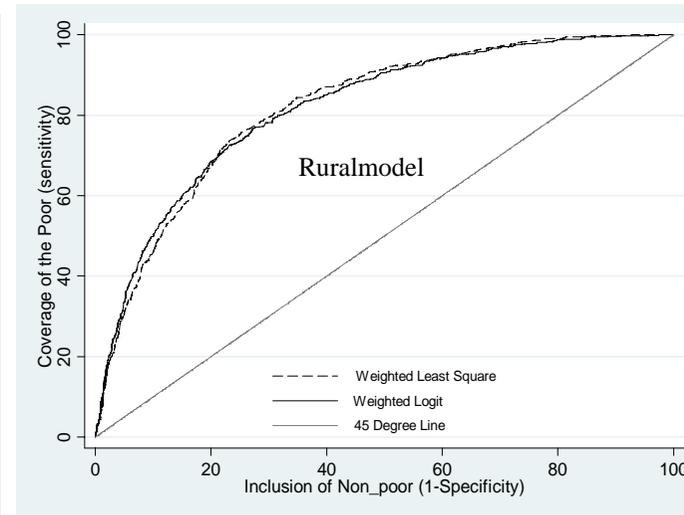


Figure 10: ROC curves of the rural model (extreme line)
Source: Own results based on Malawi IHS2 data.

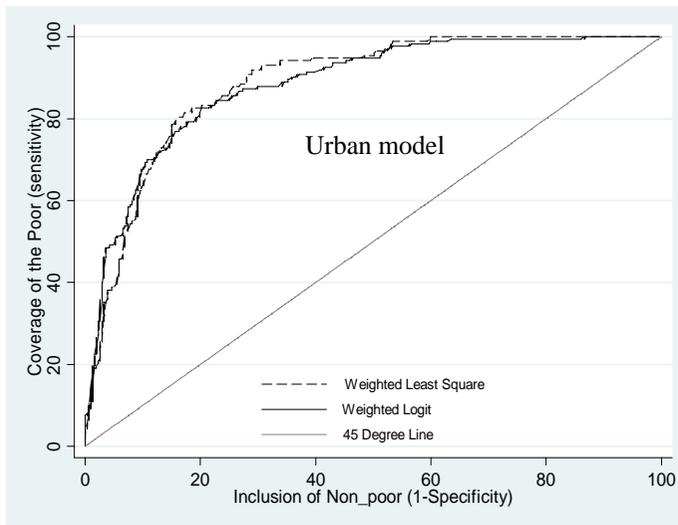


Figure 11: ROC curves of the urban model (international line)
Source: Own results based on Malawi IHS2 data.

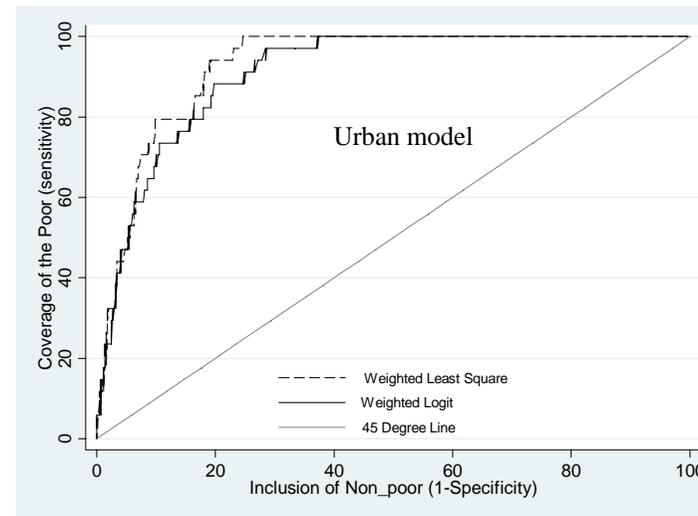


Figure 12: ROC curves of the urban model (extreme line)
Source: Own results based on Malawi IHS2 data.

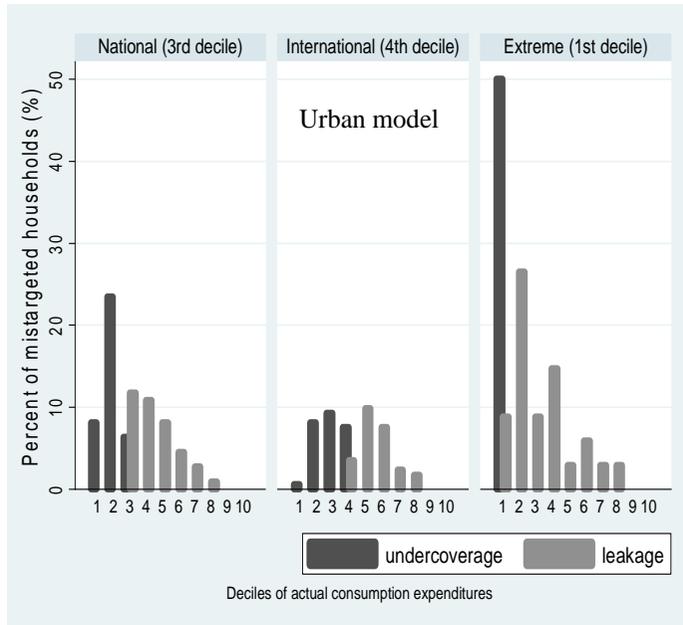


Figure 13: Targeting error distribution by poverty line (WLS)
 Source: Own results based on Malawi IHS2 data.

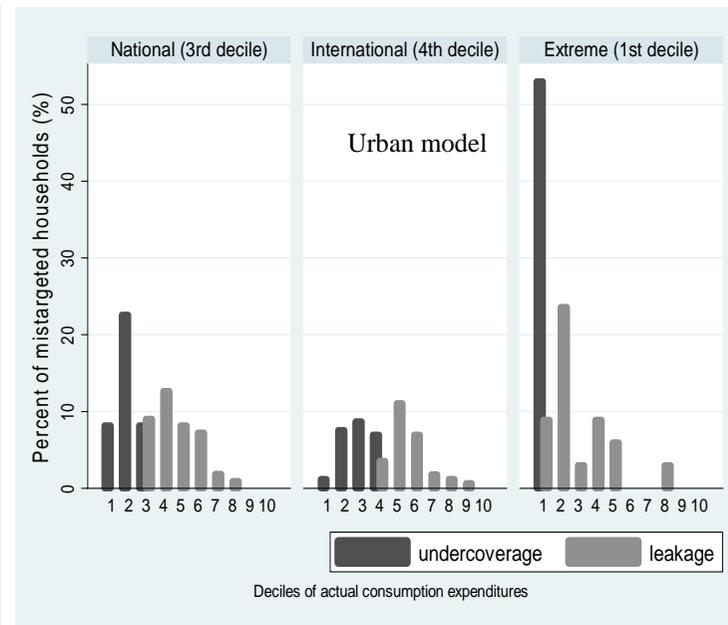


Figure 14: Targeting error distribution by poverty line (WL)
 Source: Own results based on Malawi IHS2 data.