Operational poverty targeting by means of proxy indicators

– the example of Peru –[1]

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Abstract

The measurement of per capita daily expenditures which are compared with a monetary poverty line is the most widely used approach regarding poverty assessment. It is, however, based on the implementation of time and cost-intensive household surveys and, therefore, not an operational method for targeting poor households with development services. The paper shows how to identify an alternative poverty assessment tool for Peru. It consists of a maximum of 15 powerful predictors of per-capita household expenditures selected out of a wide range of indicators from different poverty dimensions such as education, assets and housing characteristics. By applying the maximizing-R-squared regression technique to identify the best 5 to 15 predictors, we avoid an arbitrary indicator selection and the application of external weights. In a second step, an innovative approach based on the percent point function of the predicted expenditures is used for the poverty classification of households. The resulting poverty classification of households, as validated by different accuracy measures and their 95% confidence intervals, reveals that the 15 indicator tool correctly identifies over 81% of the poor households when taking the national poverty line as the relevant benchmark. The high accuracy in terms of its predictive power is confirmed by out-of-sample tests and suggests that the tool is an interesting alternative to the collection of detailed expenditure data. Before employing the tool in practice, the indicators still have to be tested for their robustness across time and then transformed to a short, focused questionnaire suitable for both ex-ante poverty targeting and ex-post impact assessment.

JEL subject codes:

I3 Welfare and Poverty, C8 Data Collection and Data Estimation Methodology

Keywords:

Poverty indicators, targeting, expenditure predictions, percent point function, Peru

1. Introduction

Our understanding and measurement approaches regarding poverty have considerably improved during the last decades. This development implies that since the capability concept of poverty at the latest (Sen, 1985; 1988; Nussbaum, 1995; 2000; Alkire, 2002), we can no longer measure monetary income or expenditures and seriously claim that we are assessing well-being in a comprehensive way. However, in view of the great challenges involved in transferring holistic poverty concepts to practical poverty assessment, money-metric approaches continue to play a vital role in political decision-making and evaluations.

The money-metric dimensions of poverty measurement have still not been sufficiently investigated in order to provide generally accepted blueprint solutions. The implications are alarming. The lack of reliable low-cost tools for poverty assessment makes it difficult to determine whether development programs meet their poverty alleviation targets. The old concern among donors, governments and practitioners about their success in reaching the poor has been re-enforced by the time-related urgency for effective action reaching the context of the Millennium Development Goals. And it has in some cases provoked consideration of targeting goals in national legislation such as the Microenterprise for Self-Reliance Act passed by the US Congress in 2000.

The objective of this paper is to contribute to the time and cost-saving employment of money-metric minimum thresholds in operational poverty targeting and impact assessment. With respect to the terminology of the capability approach, we explicitly refer to "expenditure poverty," i.e., deprivation at the household level respecting food and non-food goods and services used as economic proxies for selected achieved "functionings." We critically note that we, therefore, neglect to establish whether every individual has and uses the opportunity to make choices and whether the observed "functionings" are the desired outcomes of these choices.

We propose a tool that makes it possible to estimate household expenditures as accurately as possible by means of a set of proxy indicators that are validated by diverse accuracy measures and their confidence intervals. We avoid not only an arbitrary indicator selection and the application of external weights, both common in most of the asset and housing indices currently used (cf., e.g., Gibbons and DeWit, 1998; Deutsch and Silber, 2005), but also use an innovative approach for the poverty classification of households based on the percent point function of their expenditures. Section 2 presents the model, data and methodology used for the tool identification and their evaluation, Section 3 is devoted to the results, Section 4 discusses the strengths and limitations of the proposed poverty tool and Section 5 presents the conclusions.

2. Methods

Poverty assessment tools for a given country consist of suitable sets of a few indicators characterized by a high explanatory power of per-capita daily expenditures, the poverty benchmark measure used in this study.

<u>The identification of proxy indicators of poverty</u>

The tool identification is based on model (1) that regresses the logarithm of per capita daily expenditures (y_i) of household i on a set of variables (x_i) in order to identify the sets of the best 5, 10 and 15 poverty indicators:

$$\ln(y_i) = ßx_i + \mu \qquad (1),$$

where $x_i = \{x_1, x_2, ..., x_{142}\}$, and μ is the error term that describes the unobserved expenditure components that will affect the household's expenditure level in the future (idiosyncratic error) as well as the noise due to misspecifications of the empirical model (model error).

We used the maximizing-R-squared-regression technique (MaxR) that identifies sets of consecutively increasing numbers of indicators while maximizing the explained variance R^2 in every step. The only restriction we impose is that, in all iterations, we force nine control variables into the model (see Appendix 1). They ensure that the estimated coefficients are controlled for regional agro-ecological, cultural and socioeconomic differences as well as for demographic factors known as powerful factors influencing household expenditures (cf., e.g., Ravallion, 1992). The best 5, 10 and 15 indicators (not counting the control variables) from all possible sets of 1 to 142, are defined as those identified in step 14 (where $x_i = \{x_1, x_2, ..., x_5\}$ plus nine control variables), step 19 (where $x_i = \{x_1, x_2, ..., x_{10}\}$ plus nine control variables) and step 24, respectively. This way, three tools are obtained whose objective weights, which are necessary for the prediction of household expenditures, result from the regression coefficients.

The data

Depending on the richness of the available data, indicator-based targeting makes it possible to consider different poverty dimensions. We use the most recent living standard measurement survey (LSMS) for Peru from the year 2000,[2] which contains the following poverty dimensions:

- demographics (age, marital status, household size); ethnic and religious affiliation
- illness and disability;
- socioeconomic status (education, occupation);

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[2] The survey is called "Encuesta Nacional de Hogares sobre Medición de Niveles de Vida (ENNIV)" and was conducted by the "Instituto Cuánto" (Lima, Peru) in 2000.

- assets (land, animals, farm assets, household durables);
- housing (ownership status, size, type of material, amenities);
- access to communication (internet, telecommunications);
- credit and financial assets (financial accounts);
- selected single expenditure items (clothing, remittances).

As a household's human capital as well as productivity constraints caused by illness are determined by the number and composition of its members, we introduce demographic variables, the most important of which are included in the control variables. Education itself is introduced in the form of a broad range of ordinal and binary variables for the different sex and age groups in the household. We consider the specific human capital in terms of personal knowledge and income-generating capacities by various occupation dummies, aware that they additionally reflect exogenous labor market responses to human capital. In these categories, indicators related to the head of the household are calculated separately from those of the remaining household members. Male and female household members are treated separately as well.

Variables on the ownership, number and value of the household durables, farm assets and/or housing characteristics represent the physical capital of a household and are widely used in Asian microfinance institutions' targeting instruments and as welfare proxies in various socio-economic studies (cf., e.g., Sahn and Stifel, 2000; Filmer and Prichett, 2001; Deutsch and Silber, 2005; Gibbons and DeWit, 1998). A detailed exploration of the survey data allows the construction of 142 potential predictors.[3]

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[3] An exhaustive exploration of the data allows the calculation of nearly 400 potential predictors, many sub-groups of which measure the same phenomenon. By retaining only the most powerful ones from each sub-group (we call this in-dimension pre-selection by MaxR) and by excluding variables with measurement error and all those that are too

The household classification

The identified indicator sets are tested for their accuracy in predicting the poverty status of the households. As the standard benchmark of reliable accuracy we choose i) the national poverty line of Peru z_n (hereafter referred to as identifying the 'poor') and ii) the corresponding expenditure cut-off of the bottom 50% of the population below this line, i.e., the median poverty line z_m, as an even stricter definition of poverty (hereafter referred to as identifying the 'very poor').

Due to the geographic diversity, the national poverty line as well as our alternative median poverty line are disaggregated into seven regional ones. Both lines are listed in Table 1 with the corresponding poverty headcounts for each geographical domain.

Table 1 : Comparison between the national poverty line A) and the median poverty line B) with the corresponding poverty headcounts for the seven regions in Peru

Expenditures May 2000 **Region**	**A) Daily national poverty line** **(Soles/ pers./ day)**	**Poverty headcount** **(percent)***	**B) Daily expenditures equivalent to 50% < national poverty line** **(Soles/ pers./ day)**	**Poverty headcount** **(percent)***
Lima Metropolitan	7.75	45.2%	5.48	22.6%
Urban Coast	6.41	53.1%	4.29	26.6%
Rural Coast	4.35	64.4%	2.78	32.2%
Urban Highland	5.51	44.3%	3.70	22.2%
Rural Highland	3.61	65.5%	2.18	32.8%
Urban Lowland	5.32	51.5%	3.51	25.8%
Rural Lowland	3.71	69.2%	2.39	34.6%
Total poor (national aggregate of headcounts)		**54.1%**		**27.1%**

Source: Own calculations based on ENNIV, 2000.

closely correlated in terms of variance inflation factors above 10 or bivariate correlations above 0.65, the initial number of indicators was reduced to 142. We do not present here the detailed derivation and pre-selection of indicators due to space. This information as well as the summary statistics of all variables are available on request.

* The poverty headcount corresponds to the official figures based on ENNIV from 2000, first published by Webb and Fernández 2003

In order to test the resulting tools for their poverty accuracy, the predicted household expenditures are transferred into a binary variable that classifies each single household as either (very) poor or non-poor.

In contrast to previous work by Zeller et al. (2005) in which the poverty rates were calculated by comparing the predicted household expenditures $\hat{\beta} x_i$ in equation (1) directly with the poverty line, we opt for an approach that indirectly takes the unknown error term μ into account. By doing this, we consider that the residuals might contain additional information on immeasurable poverty determinants and avoid biased estimates of poverty rates (cf. also Hentschel et al., 2000; Ravallion, 1998).[4] We derive the poor/non-poor classification from "percentile corrected" prediction values based on the empirical cumulative distribution or percent point function of the log of the observed daily household expenditures $\ln(y_i)$. In order to derive this percent point function, the household expenditures – both the observed and predicted – are ranked and quasi-normalized (from 0 to 1) by means of the corresponding cumulated population share of each household.

[4] The simple approach based on $\hat{\beta} x_i$ compared with the corresponding poverty line results in a considerable underestimation of the predicted poverty rates, in particular when employing the stricter median poverty line.

Let F_r be the empirical cumulative distribution function of the observed expenditures $\ln(y_i)$, and let F_p be the empirical cumulative distribution function of the predicted expenditures $\ln(\hat{y}_i)$. The "percentile corrected" predicted expenditures $\ln(\hat{y}_{c_i})$ are defined as:[5]

$$\ln(\hat{y}_{c_i}) = F_r^{-1}(F_p(\ln(\hat{y}_i))) \qquad (2).$$

These corrected expenditures are compared to the corresponding poverty line z, below which a household is defined as (very) poor. Alternatively, the poverty line itself can be "percentile corrected" in order to be directly applicable to the empirical cumulative distribution function of the predicted expenditures F_p. This provides the possibility of expenditure predictions using the poverty assessment tool in independent, new samples without the need for information on observed expenditures. The percentile-corrected poverty line z^* is defined as:

$$z^* = F_p^{-1}(F_r(z)) \qquad (3).$$

It is derived from a comparison of the percent point function of the observed expenditures F_r to the true poverty headcount and is defined as the value of observed expenditures that corresponds to the household closest to the poverty headcount, as illustrated in Table 2.

[5] This approach is geared to the procedures proposed by the poverty mapping literature, in particular the approach by Hentschel et al. (2000) who use the cumulative standard normal distribution function of expenditures from which they derive the probability that a household is poor. In order to circumvent the problem of transforming these probabilities into a poverty dummy for each household and to account for non-normality of the expenditure distribution, we opt for the percent point function that makes it directly possible to establish a poor/non-poor classification based on the actual poverty headcount as cut-off point. A similar approach was proposed by Ahmed and Bouis, (2002) who use a flexible expenditure cut-off to force the poor/non-poor classification to minimize exclusion errors.

Table 2: Illustration of calculating a "percentile corrected" poverty line based on the empirical cumulative distribution function of the observed daily household expenditures

Household no.	Ranked observed expenditures per capita in Soles (y*)	Cumulative weight of household	Cumulative expenditure distribution (Y*)	Y*	Poverty classification
1	0.81	5,044	5,044/ 710,655	0.01	Poor
2	0.93	18,565	18,565/ 710,655	0.03	Poor
…	…	…	…	…	Poor
x	0.98 =**z***, given that Y* matches observed poverty headcount	191,877	191,877/ 710,655	**0.27** assuming that this matches observed poverty headcount	Non-poor
…	…	…	…	…	Non-poor
3977	2.26	710,655	710,655/ 710,655	1	Non-poor

Testing the tools for their accuracy

The following accuracy measures and prediction errors are potentially relevant when validating the tools (for details and discussion, cf. IRIS, 2005 and Hoddinott, 1999):

– overall accuracy: sum of correctly predicted poor and non-poor as a proportion of all;

– poverty accuracy: sum of correctly predicted poor as a proportion of the total poor;

– undercoverage (exclusion error): sum of actual poor wrongly classified as non-poor as a proportion of the total poor and

– leakage (inclusion error): sum of actual non-poor wrongly classified as poor as a proportion of the total poor.

On the assumption that a policy maker is interested in both correctly targeting the (very) poor by identifying the households individually and in reaching a target population similar in size to the actual poverty headcount, the IRIS Center proposes an alternative accuracy criterion:

– Balanced Poverty Accuracy Criterion (BPAC), defined as the poverty accuracy minus the absolute difference between undercoverage and leakage, all of them as given above (IRIS, 2005).[6] We base our tool validation on BPAC as a summary accuracy measure.

Confidence intervals and out-of-sample test

The tool identification was undertaken with two-thirds of the original LSMS sample, i.e., 2611 randomly drawn households out of 3977. For each of the resulting accuracy criteria, a 95% confidence interval was calculated to test the reliability of the sample and the resulting accuracy values. The confidence intervals are derived by a bootstrapping procedure based on 1000 resampled datasets of the same size.

In order to test the robustness of the expenditure predictions achieved by the identified indicator sets, we conducted an independent out-of-sample test with the remaining one-third of the original sample. The test consists of the projection of expenditures by means of the corresponding indicators with their respective parameters resulting from the in-sample regression analysis. The coefficients are introduced in the out-of-sample data, and all of the corresponding accuracy measures are calculated as usual.

3. Results

The methodology implies that the sets of best regressors are statistically determined by the search for the best model fit. The term 'best' indicator set should, therefore, not be

[6] Note that this measure would still allow very high undercoverage and leakage figures without reducing the poverty accuracy, provided that undercoverage and leakage errors are equal in size and cancel each other out. To correct for this, we added a slightly different indicator called Focused Poverty Accuracy Criterion (FPAC) defined as poverty accuracy minus leakage. It directly deteriorates in case of any misclassification error, thus neglecting the policy objective of targeting a population similar in size to the "true" poor population share. Our results show that the ranking of tools with the FPAC measure is consistent with the tools found best for maximizing the BPAC measure.

misunderstood as being best in terms of any of the accuracy measures. We show the different tests for accuracy in the second part of this section.

The resulting tools

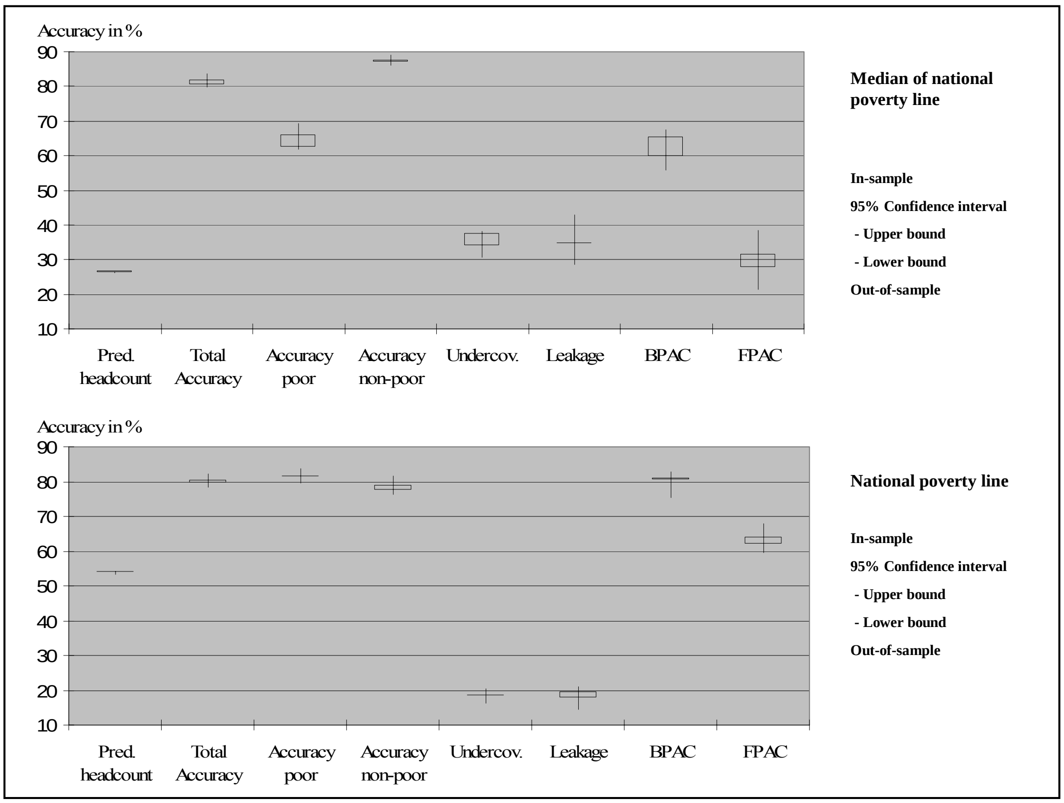
Appendix 1 shows the three poverty assessment tools with their respective parameter estimates, all of which are highly significant at $P < 0.001$. The goodness of fit of the three tools in the form of the adjusted R^2 value increases with the number of indicators and ranges from 0.722 in the first tool to 0.754 in the third one. As this study is not concerned with the causal determinants of expenditure poverty, we do not worry about endogeneity nor comment on the magnitude of the regression coefficients as long as their direction of influence conforms to theory.

The main finding refers to the multidimensional character of all of the three tools. They consist of a balanced composition of variables representing the dimensions of selected expenditures, education, assets and communication, in addition to housing in two of the three tools.

Accuracy results of the different tools

As expected, the best 15 set achieves the highest accuracy values and lowest misclassification errors among the three tools although the decrease in accuracy of the smaller indicator sets is negligible, indicating that already the best 5 set achieves satisfactory poverty predictions. The obtained tool of 15 indicators is evaluated as depicted in Graph 1 under the two scenarios determined by the two poverty lines presented in Table 1 (for the detailed results of the best 5 to best 15 sets, see Appendix 2). The in and out-of-sample accuracy values are depicted by the upper and lower horizontal border of a box or appear as a single horizontal line in case of very similar values achieved out-of-sample. The in-sample BPAC value of 81.14% under the national poverty line is achieved by a high accuracy in correctly identifying 81.76% of the poor, reduced by a small difference between the inclusion and exclusion errors, i.e., leakage and undercoverage. The corresponding confidence interval [75.44; 82.72], illustrated in the form of a vertical line, indicates that the in-sample value is closer to the upper bound of the interval, but the equally high out-of-sample BPAC value of 80.50%, confirms the robustness of this in-sample estimate.

Graph 1: Evaluation of the best 15 indicators through different accuracy measures under the scenario of two different poverty lines



In the case of the strict median poverty line, the accuracy among the poor is in particular much lower, thus resulting in higher misclassification errors and a generally lower BPAC with a considerably wider confidence interval [55.85; 67.39] than when the national poverty line is employed. This observation is due to the fact that the tool's ability to correctly identify the poor increases with the percentage of poor in the sample, which is the case when using the higher poverty line identifying more people as poor.

4. Discussion

The resulting best tool should be as accurate as possible in predicting the poverty status of the population and – in order to be suitable for implementation – be practical in addition, i.e., indicators should be easy to ask, to respond and to verify under field conditions. From a viewpoint of practicability, it might be worth thinking about an alternative tool that bans the variable on the value of all household durables from the indicator list because it demands an extended questionnaire section about the number and value of all household durables. In addition, this indicator (as well as all remaining monetary variables) is difficult to verify. Of course, an exclusion of such powerful monetary proxies reduces the accuracy of a tool.[7] This implies the logical trade-off between the predictive power of a tool and its practicability.

Regardless of these considerations, in our case where the achieved accuracy levels (especially in case of the national poverty line) are very high and do not differ much between the tools, any of the indicator sets could be proposed to a policy-maker depending on the budgetary constraints.

Compared to a detailed expenditure questionnaire, a tool of 5 to 15 indicators represents a short and low-cost option for poverty assessments. The 15 indicator tool achieves the highest accuracies under a policy scenario such as that of the US Congress Act that demands microfinance projects to target the 27% 'very poor' as defined by the median poverty line. Particularly in case of this stricter line, the percent point function approach for the poverty classification of households proposed here performs much better in terms of a BPAC confidence interval of 56 to 67% than a simple classification based on the direct expenditure calculation $\hat{\beta} x_i$ would do (yielding a BPAC interval of a much wider span and below 50%).

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[7] In our case, the replacement of all of the monetary variables (including the summary value of all household durables) by other (next-)best indicators reduces the BPAC value in the in-sample from 63.79 to 58.46 for the best 5 and from 65.36 to 62.53 for the best 15 set, both of them under the scenario of the median poverty line.

5. Conclusions

We present a methodology for identifying an operational poverty assessment tool for Peru and show how to make concrete statements on its performance based on different accuracy measures. In the case of using the national poverty line as the poverty benchmark, the proposed tools consisting of 5 to 15 indicators achieve an accuracy of correctly predicting the poverty status of 79 to 84% of the poor (95% confidence intervals of poverty accuracy). In order to be employed practically, the indicators should be transformed to a short, focused poverty questionnaire as an alternative to the cost and time-intensive collection of detailed expenditure data. The tool makes it possible i) to identify ex ante those households that lie below a certain pre-defined minimum threshold and should, therefore, be offered to participate in a development project or program and ii) to assess ex post the impact of such intervention on the households' current expenditure level.

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Appendix 1: The three best indicator sets and their parameter estimates on predicted daily household expenditures per capita

Best 5, Tool 1		Best 10, Tool 2		Best 15, Tool 3	
Adjusted R^2	0.722	Adjusted R^2	0.745	Adjusted R^2	0.754
Intercept	1.655***	Intercept	1.822***	Intercept	2.256***
Household size	-0.241***	Household size	-0.235***	Household size	-0.291***
Household size squared	0.010***	Household size squared	0.009***	Household size squared	0.011***
Age of head of hh	0.002***	Age of head of hh	0.002***	Age of head of hh	0.001**
Household lives in Urban coast	-0.097***	Household lives in Urban coast	-0.090***	Household lives in Urban coast	-0.092***
Household lives in Rural coast	-0.354***	Household lives in Rural coast	-0.322***	Household lives in Rural coast	-0.292***
Household lives in Urban highlands	-0.214***	Household lives in Urban highlands	-0.215***	Household lives in Urban highlands	-0.207***
Household lives in Rural highlands	-0.477***	Household lives in Rural highlands	-0.418***	Household lives in Rural highlands	-0.393***
Household lives in Urban lowlands	-0.179***	Household lives in Urban lowlands	-0.169***	Household lives in Urban lowlands	-0.157***
Household lives in Rural lowlands	-0.358***	Household lives in Rural lowlands	-0.365***	Household lives in Rural lowlands	-0.337***
Log of value of video tapes	0.041***	Log of value of video tapes	0.030***	Log of value of video tapes	0.024***
Log of annual clothing exp p.c.	0.032***	Log of annual clothing exp p.c.	0.029***	Log of annual clothing exp p.c.	0.030***
Log of value of durables	0.123***	Log of value of durables	0.106***	Log of value of durables	0.094***
Household has fixed telephone	0.264***	Household has fixed telephone	0.234***	Household has fixed telephone	0.222***
Average years of education of all members	0.035***	Average years of education of all members	0.030***		
		Floor material: dirt/ other	-0.104***	Floor material: dirt/ other	-0.098***
		Log of remittances sent	0.024***	Log of remittances sent	0.024***
		Household owns cell phones	0.237***	Household owns cell phones	0.205***
		Number of members using internet	0.090***	Number of members using internet	0.085***
		Household uses no or inferior cooking fuel	-0.284***	Household uses no or inferior cooking fuel	-0.365***
				Household uses wood/ carbon as cooking fuel	-0.122***
				Log of value of vacuum cleaners	0.027***
				Light source: candles	-0.162***
				Number of members that can read and write	0.042***
				Number of members with sup./ univ./post-grad. educ.	0.050***
				Number of shovels/ rakes owned	0.014***

Level of statistical significance: $^{***}P < 0.001$.

Appendix 2: Evaluation of the best 5 and best 10 indicators through different accuracy measures using two different poverty lines, including 95% confidence intervals and out-of-sample tests

Poverty line used	Robustness tests	Type	Actual poverty headcount	Predicted poverty headcount	Total accuracy	Poverty accuracy	Non-poverty accuracy	Under-coverage	Leakage	Balanced poverty accuracy BPAC	Focused poverty accuracy FPAC
Median of national	In-sample	Best 5	26.24	26.27	81.02	63.88	87.12	36.12	36.21	63.79	27.67
	95% confidence interval			26.14 26.60	79.03 82.88	60.17 68.13	85.58 88.59	31.87 39.83	29.88 44.36	54.28 65.83	18.75 35.85
	Out-of-sample		27.08	26.27	80.15	61.85	86.95	38.15	35.14	58.85	26.72
Median of national	In-sample	Best 10	26.24	26.45	81.56	65.26	87.36	34.74	35.53	64.47	29.73
	95% confidence interval			26.16 26.61	79.66 83.53	61.31 69.08	85.85 89.09	30.92 38.69	28.66 43.35	55.70 67.04	20.74 38.33
	Out-of-sample		27.08	26.32	81.05	63.62	87.53	36.38	33.58	60.82	30.04
Median of national	In-sample	Best 15	26.24	26.44	82.02	66.11	87.67	33.89	34.64	65.36	31.47
	95% confidence interval			26.13 26.60	79.91 83.72	61.76 69.40	85.98 89.13	30.60 38.24	28.44 42.89	55.85 67.39	21.42 38.41
	Out-of-sample		27.08	26.36	80.38	62.43	87.04	37.57	34.89	59.75	27.55
National	In-sample	Best 5	54.27	53.90	79.58	80.84	78.07	19.16	18.48	80.16	62.36
	95% confidence interval			53.42 54.29	77.70 81.82	78.69 83.15	75.67 81.03	16.85 21.32	15.02 22.12	74.86 82.28	58.44 66.69
	Out-of-sample		53.76	54.11	79.65	81.40	77.62	18.60	19.25	80.75	62.15
National	In-sample	Best 10	54.27	53.83	80.09	81.25	78.71	18.75	17.95	80.45	63.30
	95% confidence interval			53.41 54.28	77.87 81.93	78.81 83.37	75.88 81.13	16.63 21.20	14.96 21.65	74.80 82.25	58.87 67.01
	Out-of-sample		53.76	54.11	79.05	80.85	76.97	19.15	19.81	80.19	61.04
National	In-sample	Best 15	54.27	53.93	80.54	81.76	79.10	18.24	17.62	81.14	64.14
	95% confidence interval			53.43 54.30	78.42 82.28	79.53 83.80	76.37 81.71	16.20 20.47	14.38 21.16	75.44 82.72	59.62 67.78
	Out-of-sample		53.76	54.21	79.49	81.34	77.34	18.66	19.50	80.50	61.85