How robust are indicator based poverty assessment tools over time? Empirical evidence from Central Sulawesi, Indonesia

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Abstract
Eradicating poverty is one of the most urgent concerns of development policies. Organisations aiming at reducing poverty need simple and stable tools to detect poor households. Using data from Central Sulawesi, Indonesia, this study aims to test first whether two indicators sets for poverty assessment found in 2005 are still capable in predicting absolute poverty and second, if the indicator composition remains robust over time.
Data from two household surveys were used: In 2005 we surveyed 264 households in the vicinity of the Lore Lindu National Park in Central Sulawesi to obtain indicators of poverty and to derive the daily per capita consumption expenditures. In total 280 indicators were sampled. Two different multivariate regression models were fit to this data-set. One model (Model 1) included all sampled indicators and the other one (Model 2) contained only easily verifiable indicators as ranked by local staff. Each of the models yielded a different set of 15 indicators that predicted poverty best. In 2007, we conducted an additional survey with the identical questionnaires in the same households. We used the data from 2007 to estimate the poverty status of the households with the indicators derived in 2005. Furthermore, we applied the same regression models again to detect changes in the indicator composition.
In Central Sulawesi, almost 20% of the rural population was identified as being very poor in the years 2005 and 2007. Regarding the prediction power of the 2005 indicators we found that the prediction power for 2007 mainly was influenced by the error of over-predicting the poor. When re-estimating the models, the accuracy levels remained similar, but the indicator composition changed.

1. Problem setting

Although the first millennium development goal of the United Nations is to reduce extreme poverty and hunger by half until 2015 (United Nations 2008), that goal has yet to be achieved and poverty remains a pervasive problem in many countries. In general, poverty reduction is one of the main goals of development policies, programs and projects (e.g. Zeller et al. 2001, Collier and Dollar 2002). In Central Sulawesi we found that almost 20% of the households are very poor, i.e. live on less than $1 US purchasing power parities (PPP) per day. In contrast the Human Development Reports (2007/2008) gives an average poverty headcount of 7.5% for entire Indonesia.

To better target absolute poor households easy applicable tools for poverty assessment are needed. For non-governmental organisations (NGOs) and other stakeholders concerned with poverty reduction it is particularly important that tools which enable the detection of absolute poor households are low in costs and contain indicators which are robust over time. Several attempts in poverty assessment try to meet poverty as multidimensional phenomenon in contrast to a pure measure of inadequate income or expenditures (Osmani 2003). In his book "Development as freedom" (1999) Sen argues that poverty rather is a deprivation of basic capabilities and not only a matter of the lowness of income. Nevertheless, he also admits that low income is one of the major causes of poverty in the sense that it is often a reason for capability deprivation. Hence, it is necessary to use approaches which account for low incomes and other forms of deprivation.

Most poverty assessments done in the last 25 years referred to relative poverty (Zeller 2004). Until now relatively few attempts have been made to assess absolute poverty. There were several studies on proxy means test (e.g. Ahmed and Bouis, 2002 and Grosh and Baker 1995). Wodon (1997) used ROC curves to compare the performance of targeting indicators to identify the poor. One recent approach used is to assess a household's poverty status via food security scales. Three different scales – non food insecure, moderately food insecure and severely food insecure – are used to predict daily per capita expenditures. This tool faces the problem that food insecurity is not always identical with (income) poverty (Alcaraz V. and Zeller 2008). Another approach to assess poverty was developed by the IRIS[1] centre at the University of Maryland in collaboration with the US Agency for International Development (USAID). These organisations developed and tested different poverty assessment tools, which are meant to meet the needs of poverty reduction projects, especially those dealing with micro enterprises. These tools were developed in order to meet the requirements of the US Congress, which mandated USAID to develop and certify a low-cost and easy-to-implement poverty assessment tool with a high accuracy (http://www.povertytools.org). The methodology used is avoiding an arbitrary selection of indicators as well as the application of external sampling weights (Johannsen, 2006). A challenge of all these tools is their robustness over time.

2. Objectives

The aim of the study is to test these new tools for the assessment of absolute poverty. Two very promising types of regression models are tested in Central Sulawesi. The methodology used is the same the IRIS Centre employed during their analysis. For the study two sets of household data are used. In 2005, we conducted research to identify two sets of 15 indicators each for poverty assessment in Central Sulawesi, Indonesia (van Edig 2005). We wanted to compare the capability of the models in predicting very poor households with the observed poverty headcounts.

In 2007, we conducted the same survey again to test the identified poverty assessment tools (PATs) regarding their capability in poverty prediction two years later and therefore their robustness over time. Furthermore, we re-estimated the models using the 2007 data set to detect a new sets of indicators, which we compared to the sets identified in 2005. With this we want to observe changes in the indicator composition of the tools.

[1] IRIS is a research and advisory centre at the Department of Economics, University of Maryland

3. Indicator based models for poverty assessment

The approach of indicator based poverty assessment connects indicators of different dimensions of poverty with the commonly used poverty line. In the case presented, the international poverty line of $1 US serves as the reference benchmark for the tools.

Indicators of poverty should – as the word indicator suggests - indicate a person's or household's standard of living or income and yield information about the social conditions of the poor. Similar to poverty profiles, poverty indicators were developed later than poverty lines to measure poverty and then combining the information found with basic needs and income-related measures (Schubert 1994, Minot 2000). Poverty indicators can be a constitutive part in developing poverty reduction strategies as they improve their targeting. While the indicators vary between the subjective and objective perspectives on poverty, they are often similar in the relative and absolute approach (Lok 1995). One problem identified is that poverty indicators face difficulties in differentiating chronic from temporary poverty. For example monetary poverty is less persistent than malnutrition or low school enrolment (Baulch and Masset 2003).

A commonly used approach to assess poverty is the "construction of a poverty line and (the) computation of various measures that take into account the way in which household expenditures fall short of the poverty line" (Zeller et al. 2001, p. 3). In practice, however, total household expenditures are used as a measure to evaluate a household's living standard. Whether the household income is sufficient to meet food security and other basic needs is used as a criterion. The "basket of basic needs" or a monetary poverty line is applied. This "basket of foods and services" corresponding with the local consumption pattern and satisfying a pre-set level of basic needs for one person is constructed and ranked at local consumer prices to compute its minimum costs" (Zeller et al. 2001, p. 3-4). The value of this basket represents the poverty line, mostly in terms of daily per capita expenditure. This approach is mainly used by governments to derive their national poverty line. In this study we refer to the international poverty lines, which have been developed for international comparisons. There are two international poverty lines promoted by the World Bank. The most common and widely known is the $1 US poverty line. This poverty line standardizes the consumption across countries and is expressed in purchasing power parities which are adjusted with the consumer prices (ADBI 2009). In this paper the term "very poor" refer to this poverty line. The second international poverty is the $2 poverty line, thus two times the $1 US poverty line. To this, the term "poor" refers. Recently the World Bank adjusted the 1$ US poverty line to 1.25$ US and the 2$ US poverty line to 2.50 $ US (World Bank 2009).

In the study presented, two models for poverty assessment in Central Sulawesi, Indonesia, were tested. These models search for sets of 15 poverty indicators to predict daily per capita expenditures of a certain household. In each survey year, almost 280 indicators which acted as independent variables, were compiled from the composite questionnaire. For the first model (Model 1), every surveyed indicator could possibly be included. In the second model (Model 2), only indicators which were ranked as “easy to verify” by the Indonesian staff were included. Many of the variables from Model 1 were either difficult to survey or difficult to verify. The following two examples, out of the 15 indicators for Model 1 from 2005, should illustrate this: The subjective indicator “Household feels that its healthcare expenditures are above its needs” is very difficult to verify because of its subjectiveness. “The average clothing expenditures per capita in the last 12 months” instead is an objective indicator. Nevertheless, the required information is difficult to obtain and difficult to verify, too. Model 2 only included indicators which were “easy to verify”: E.g. the indicator “total number of rooms in a dwelling” can be obtained and verified easily by the enumerator during the interview.

Why two different models? Although, Model 1 was more likely to achieve a better accuracy performance because it used all variables, Model 2 referred to two categories of problems which might occur in the analysis of indicators. First, information might be difficult to obtain, especially regarding the aspects of time, social costs and money. Second, indicators might be difficult to verify, especially if they are recall-related (Zeller et al. 2005).

For purposes of assessing the prediction power of a regression model (or tool) for poverty assessment, we used the following measures of performance for each model (Zeller et al. 2005 /The IRIS Centre 2005):

Total Accuracy is the percentage of households whose poverty status is correctly predicted by the regression model.

Poverty Accuracy is the percentage of very poor households whose poverty status is correctly predicted by the regression model. It is expressed as a percentage of the total number of very poor households.

Non-poverty Accuracy: is the percentage of not very poor households whose poverty status is correctly predicted by the regression model. It is expressed as percentage of the total number of not very poor households.

Undercoverage represents the error of predicting very poor households as being not very-poor, expressed as a percentage of the total number of very poor households.

Leakage reflects the error of predicting not very poor households as very poor, expressed as a percentage of the total number of very poor households.

Poverty Incidence Error (PIE) is defined as the difference between the predicted and the actual (observed) poverty incidence (here headcount), measured in percentage points.

Balanced Poverty Accuracy Criterion (BPAC) is defined as the *Poverty Accuracy* minus the absolute difference between *Undercoverage* and *Leakage*, each expressed as a percentage of the total number of the very poor. When Undercoverage and Leakage are equal, the BPAC is equal to the Poverty Accuracy. BPAC is measured in percentage points.

The BPAC was introduced by IRIS "on the assumption that a budget-constrained 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 headcount" (Johannsen 2006, p. 7).

4. Data collection

Household surveys are the most important data source for poverty measurement and poverty comparison. They can provide direct information about the distribution of living standards in a society or in a certain region, for example how many households do not attain a certain consumption level. With the availability of such quantitative data, the poor can be assessed and an assessment of poverty policies can be done (Ravallion 1992).

The study used household data from two survey years. In both survey years, data were collected in 13 villages in the vicinity of the Lore Lindu National Park. In both years the same randomly selected households participated in the survey. In 2005, the models were estimated with data from 279 households. In 2007 data from 282 households were obtained. The intersection of both samples was 264 households.

Two questionnaires were completed in both years. One was a benchmark questionnaire to obtain the daily per capita consumption expenditures of each household and resembled the consumption module of the *Living Standard Measurement Survey* (LSMS) of the World Bank. Thus it had the same purpose of the LSMS which is to "collect information to describe poverty and monitor it over time" (Grosh and Glewwe 2000, p. 30). Thus, the benchmark questionnaire focused on the economic dimension of poverty.

Second, we used a composite questionnaire to derive indicators of poverty in several dimensions as poverty is a complex phenomenon.The dimensions captured were:

- demographics/household composition (age, household size etc.)
- socio-economic status (education, occupation etc.)
- selected single expenditure items (clothing, health etc.)
- housing (ownership status, materials, access to utilities etc.)

- wages (intended use of additional income)
- food consumption (superior/inferior food items)
- social capital
- self-assessment of poverty (ladder of live)
- financial assets (informal borrowing/lending)
- assets (household durables, land, animals etc.)

The composite questionnaire was developed based on the questionnaire IRIS used for their poverty assessment tool (IRIS 2004).

5. Data analysis

As to the fact that we derived 280 potential independent variables from the composite questionnaire, the amount of independent variables had to be reduced because of a lack of degrees of freedom for the model estimation. For this purpose several steps for the indicator selection were employed. Primarily, for Model 1 all indicators were grouped on different dimension of poverty such as education, food, assets etc. For each of these dimensions we ran an OLS regression which delivered indicators for the final model estimation. After this pre-selection an initial set of 86 variables remained for the model estimation. For Model 2, the number of indicators was restricted by the condition of being "easy-to-verify" leading to a total number of 90 variables. Here no further pre-selection was necessary.

In each step of the indicator selection, nine control variables were forced in the model estimation: As the human capital of a household and therefore its productivity is influenced by the household composition four important demographic variables (see e.g. Ravaillon 1992) controlled for demographic factors. Furthermore, five regional dummies controlled for agro-ecological differences. This were the same control variables as used by IRIS (Zeller et al. 2005, Johannsen 2006). For the variable selection ordinary least square regressions (OLS) and the MAXR routine implemented in SAS were used. MAXR seeks to maximize the R^2 considering all possible combinations of regressors (Johannsen 2006). For the final selection of indicators various checks and adjustments, especially regarding the sign of the coefficient of each indicator had to be done. The sign was expected to concur with the direction one would expect from theory.

Any of the variable sets found can be described as a poverty assessment tool for the purpose of identifying the poverty status of a household. The dependent variable (per capita daily expenditures) is, like any other variable defined in monetary values (as expenditures or values of assets), converted into the natural logarithm of Indonesian Rupiah (IDR). This was done as the basic assumption of linear regression models is the linearity of the relation estimated. By transforming the non-linear monetary dependent and independent variables into log linear ones the linearity in parameters is achieved and the linearity condition is assumed to be fulfilled (Kennedy 2003). All ordinal variables, such as the 'type of exterior wall of the dwelling', with lower values indicating inferior materials and higher values indicating superior materials, are converted into dummy variables for each sub-type (Zeller et al 2005).

Different regression methods, one and two-step OLS as well as one and two-step quantile regressions, were tested regarding their accuracy results. In contrast to OLS regressions, quantile regressions minimize the absolute sum of errors to the median or any other quantile. Therefore, they are also called least absolute value models (Koenker and Hallock 2001). In two step regressions, two steps of indicator selection were employed: The first step was identical to the one step regression described above. In a second step it was searched for an additional variable set to re-predict the expenditures of a sub sample which contained a higher percentage of poor households, i.e. the definitely non-poor households were excluded from the estimation. Hence, the second step should improve the accuracy among the poor (Zeller et al. 2005, Johannsen forthcoming 2009). In 2007, for model 1, the expenditures of 32% of the households were re-estimated in the second step of two step regressions. For model 2 it were 38% of all households.

When applying the tools to assess whether a household is poor or not, the predicted daily per capita expenditures of household *j* are calculated as

$$\mathrm{Y}_j = \beta_0 + \sum_{i=1}^{N} \beta_i * \chi_{j\,i}$$

were Y_j is the natural logarithm of the (predicted) daily per capita expenditures, β_0 is the intercept, β_i are the coefficients, and χ_{ji} are the surveyed values of the indicator used in the model. If the result lies over the poverty line, the household is classified as non-poor, if it lies below the poverty line the household is classified as poor.

For the one-step regression the use of this equation is straightforward. For a two-step model, it is necessary to calculate the predicted per capita expenditures in two steps. In practice this means that in the second step only those households are included whose predicted daily per capita expenditures are below a certain expenditure percentile found during the indicator selection. For the households in our study which were predicted in the first step (one-step OLS/ one-step quantile) as having less expenditures as the 32 percentile (Model 1) or 38 percentile (Model 2), a second indicator set to predict their expenditures was applied. For all other households the predicted values from the one-step regression remained in the model.

In 2007, first the indicator sets derived in 2005 were applied to the new data-set. Secondly, both models were re-estimated following the same procedure as in 2005.

6. Results

a. Poverty incidence in Central Sulawesi 2005 and 2007

In the research area, the number of very poor people, i.e. those people living below the international poverty line of $1 US, slightly decreased from 19.2% in 2005 to 18.2 % in 2007 (Table 1). The decrease in the poverty headcount is, however, not statistically significant. In contrast the number of poor, i.e. those who live on less then $2 US per capita and day, significantly increased from 46.6% to 59.1%. This finding concurs with the overall trend observed for Indonesia: The World Bank (2008) found increasing poverty rates after 2006 mainly due to increasing food prices.

Table 1. Percentage of poor households in Central Sulawesi using alternative definitions of poverty in 2005 and 2007

Poverty line	Poverty line (IDR per capita and day)		Headcount Index (%) (N=264[2])		Change (%)
	2005	2007	2005	2007	
$1 US PPP	2723	3436	19.2	18.2	1
$2 US PPP	5445	6872	46.6	59.1	12.5**

Source: own data

**Paired t-test significant at the 1% level of error probability

b. Robustness of the poverty assessment tools over time

The best accuracy performance in 2005 for Model 1 was achieved with a two-step quantile regression. When using the indicators selected in 2005 as well as their estimated coefficients with the data from 2007, the total accuracy dropped from 92.1% to 81.2%, the poverty accuracy also dropped by ca. 10 percentage points from 69.6% to 58.5%. The non-poverty accuracy declined from 95.1% in 2005 to 86.5% in 2007. As both prediction errors increased – the undercoverage from 20.4% to 41.5% and the leakage from 20.4% to 58.5% - the BPAC decreased from 79.7 to 41.6 (Figure 1).

[2] 264 households were the intersection of both samples

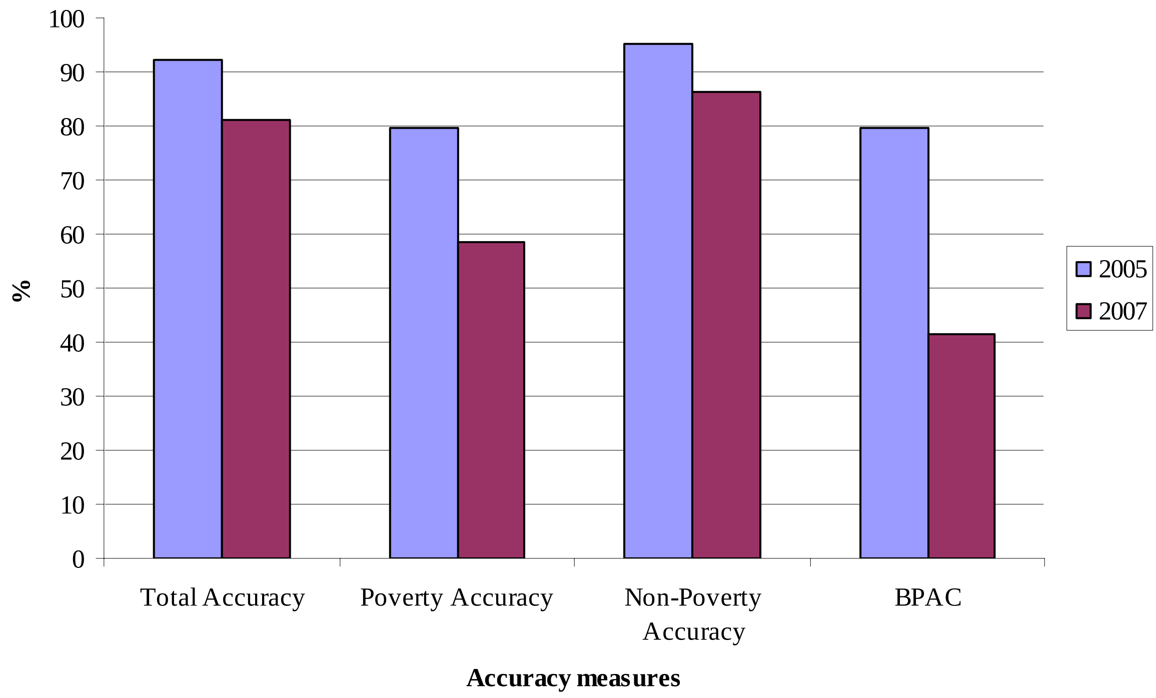

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Figure 1. Comparison of accuracy results of Model 1 2005-2007, two-step quantile regression (2005: N= 279, 2007: N=282)

To detect which of the 2005 indicator sets – with their corresponding coefficients – fitted the 2007 data-set best, we calculated the accuracy of every tested regression method, i.e. one- and two-step OLS and one- and two-step quantile. Even if the overall accuracy of two-step quantile dropped, it remained the best way to predict the daily per capita consumption expenditures of the households and therefore poverty status of the households with Model 1.

As discussed above (section 3), Model 1 faced several difficulties with the included indicators including the fact that rural households in the study area normally do not own a scale to monitor their weight. Therefore, the indicator “household member lost weight because of food scarcity” relies on their own impressions. As well, the indicator “food expenditure share of total consumption expenditures in percent” refers to questions in the composite questionnaire which asks for estimates of expenditures on food and non food categories. This indicator might therefore be biased by wrong guesses of the interviewed person. A full list of the indicators and their corresponding coefficients for the second step of two step for Model 1 regressions is provided in appendix 1.

One-step quantile regression provided the best accuracy results for Model 2 in 2005. In Figure 2, the accuracy results for this regression method are shown. The total accuracy decreased by 11.2 percentage points, but poverty accuracy only by 0.5 percentage points while non-poverty accuracy declined by 13.9 percentage points. As a result of increased leakage (leakage rose by 61.1 percentage points from 27.8% to 88.7%), the BPAC dropped from 72.2% to only 11.1%. The undercovarage stayed with 26.4% alsmost the same as in 2005 (25.9%)

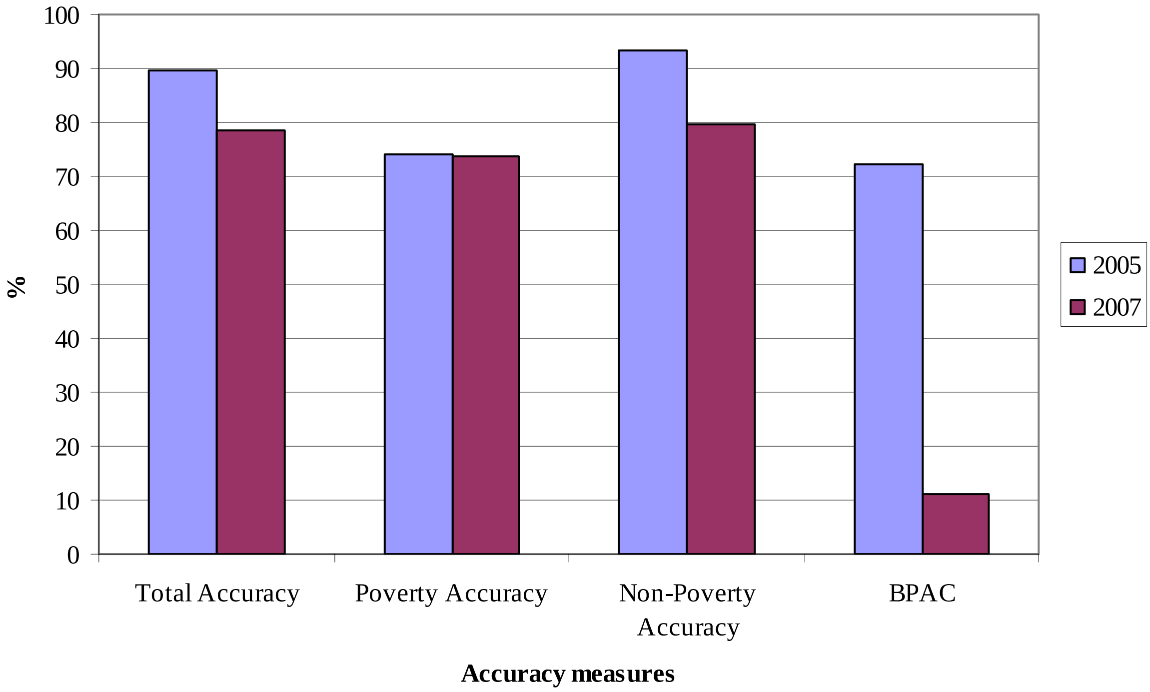

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Figure 2. Comparison of accuracy results of Model 2 (2005-2007), one-step quantile regression

As done for Model 1, we calculated all methods, i.e. one- and two-step OLS and one-and two step quantile, using 2005 indicators and coefficients to observe which method of Model 2 fitted the 2007 data set best. Thus in 2007, one-step OLS gave the best overall accuracy results (Figure 3). The increase of the BPAC (from –0.01% in 2005 to 50.94%) in 2007 can be explained with the higher poverty accuracy (44.44% in 2005 and 54.72% in 2007) and the decline of the prediction error undercoverage (from 55.56'% in 2005 to 45.28% in 2007), but also with to the increase in the error leakage from (11.11% in 2005 to 49.0% in 2007), because now both errors cancel each other out.

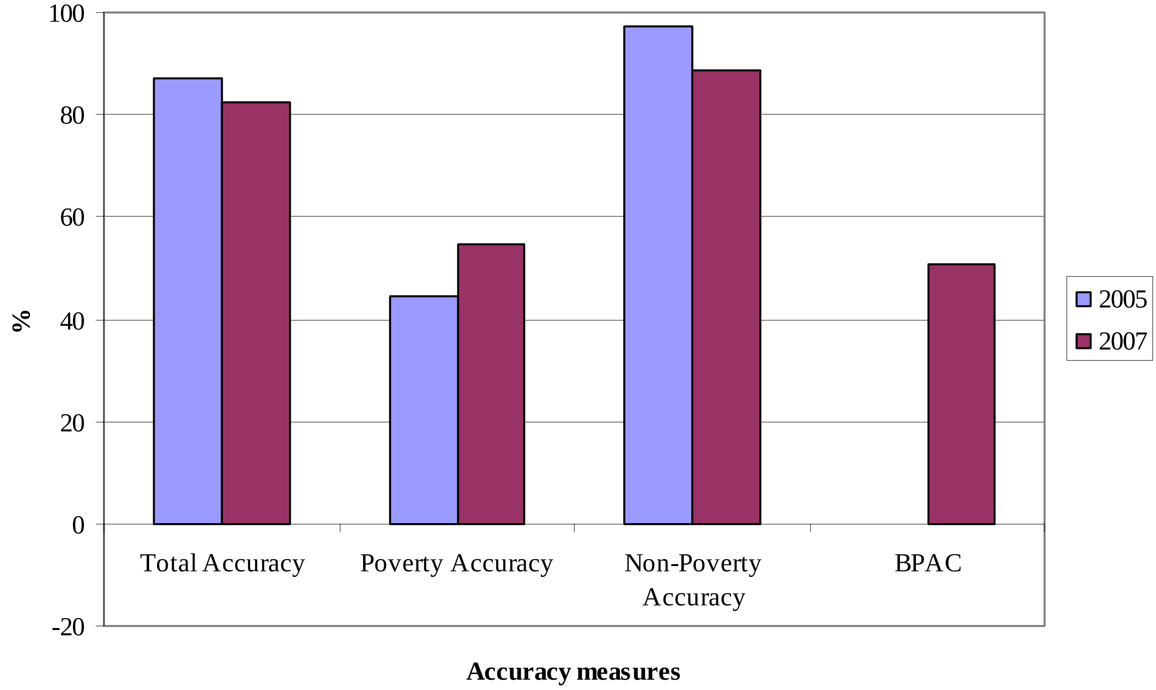

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Figure 3. Comparison of accuracy results of Model 2 (2005-2007), one-step OLS regression

The indicators in Model 2 are mostly time invariable or change only very slowly over time. The potential problem with this variable set is that it might not capture short term poverty dynamics and therefore rather detects the chronic than the transitory poor. A list of the one-step indicators and the corresponding coefficients can be found in appendix 2.

c. Robustness over time of the indicators used

Additional, we re-estimated both models to observe changes in the indicator composition. When comparing the accuracy results for Model 1 in 2005 and 2007, in both years two-step quantile regression delivered the best overall accuracy results. In general, the level of accuracy performance was approximately the same in both years. Only one-step OLS delivered a much higher BPAC in 2007 than in 2005: It increased from 3.7% in 2005 to 32.1% in 2007. Nonetheless, the accuracy performance of one-step OLS remained low (Figure 4).

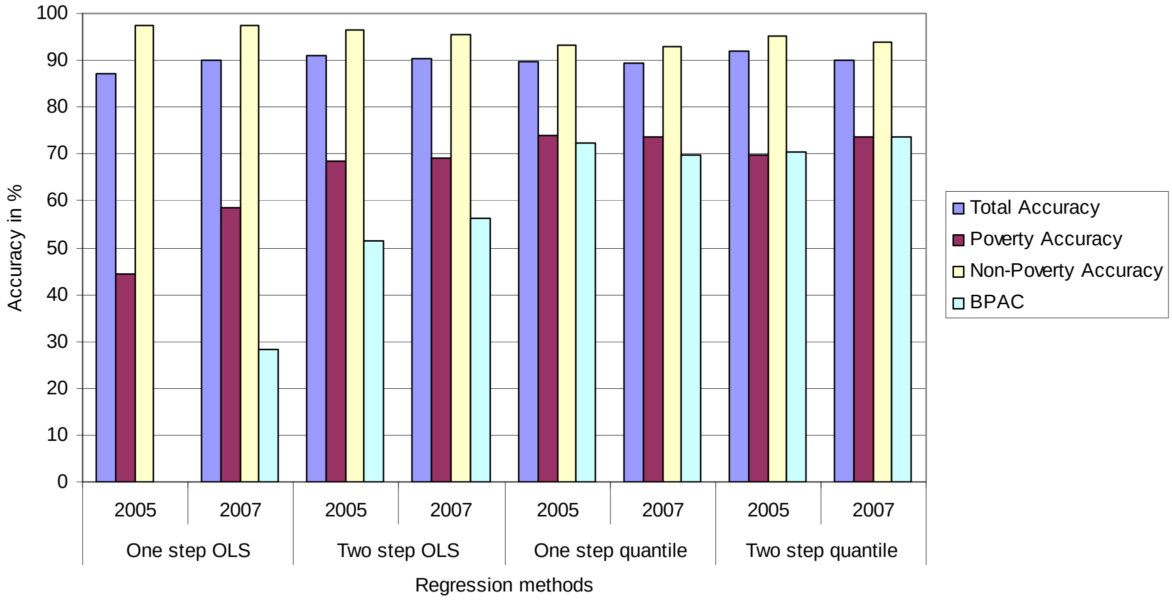

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Figure 4. Model 1 estimation comparison

Regarding the indicators included in one-step regressions for Model 1, only one of the indicators remained the same as in 2005. This is the "natural logarithm of annualised total consumption from composite questionnaire". None of the variables remained the same for the composition of the two-step variable set.

In 2005, one-step quantile regression provided the best accuracy results for Model 2. In 2007 instead, two step quantile performed somewhat better. In 2005, one-step quantile delivered a BPAC of 72.2%, which slightly decreased to 69.8% in 2007. For two-step quantile it was the opposite: in 2005 the BPAC was 70.4%, in 2007 it achieved 73.6%. These results were very close to each other. The BPAC of one-step OLS for Model 2 also increases from 0% in 2005 to 28.3% in 2007. Nevertheless, one-step OLS showed also low accuracies.

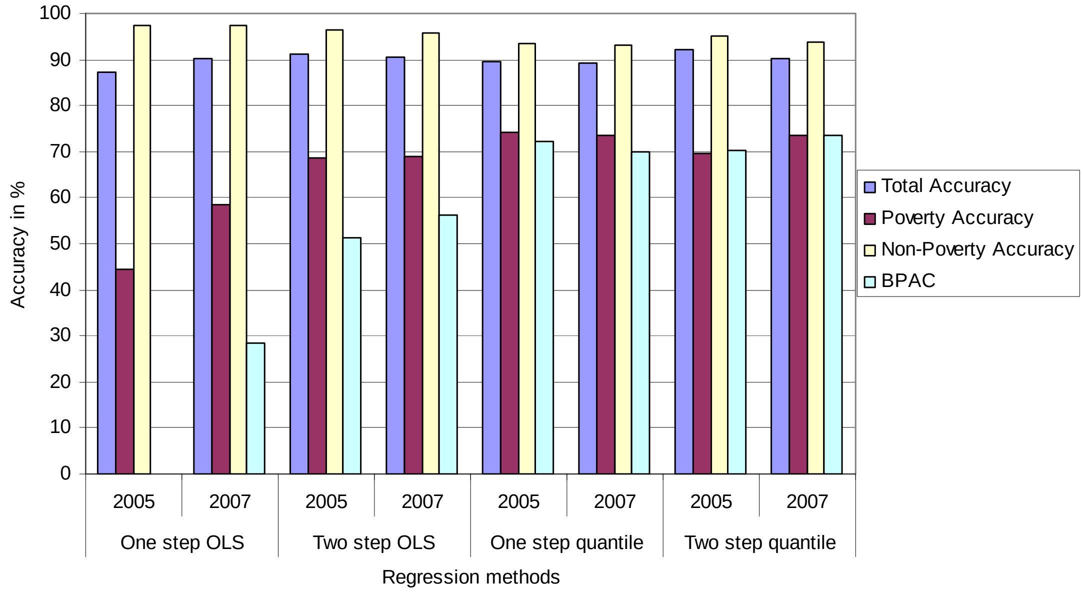

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Figure 5. Model 2 estimation comparison

For one-step regressions of Model 2 the following indicators remained the same as in 2005: “total rooms in the dwelling”, “cow ownership”, “number of trunks and suitcases owned” and “motorcycle ownership” Thus, only four indicators out of 15 were robust over time.

When comparing the indicators from two step regressions in both years, five indicators or a third remained the same: “total rooms in the dwelling”, “bicycle ownership”, “cow ownership” “household head works outside of agriculture” and “household uses other cooking fuel than collected wood”.

7. Conclusion and discussion

In 2005, when the tools for Central Sulawesi were developed, one of the biggest problems was the trade-off between the practicability of a tool and its accuracy (van Edig 2005, van Edig et al. 2007). Johannsen and Zeller (2006) also found that the exclusion of monetary indicators (as done in Model 2) reduces the accuracy of the tool. In addition, Zeller (2004) describes another problem poverty assessment has to face: the trade-off between accuracy and costs. Our results indicate another potential weakness of poverty assessment tools: their stability over time. When predicting the poverty status of households in 2007 with the indicators from 2005, the accuracy of both models dropped especially the inclusion error leakage increased. Thus, the capability of the tools two years after the configuration of the models was limited by the error of predicting non-poor households as being very poor.

We expected Model 1 to perform somewhat better because it includes many short-term indicators like the "number of days in last week any superior food (large fish, beef/pork/buffalo meat, chicken/duck or egg) was eaten" or the "natural logarithm of expenditures on other expenditures, social events and leisure in the last 12 months" (both examples from one-step regressions). These indicators tend to change with the same speed as household expenditures. Model 2 instead mostly used long-term variables like "total rooms of the dwelling" which do not change as fast as expenditures. In contrast to our expectations one-step OLS of Model 2 provided the best overall accuracy. This is opposite to the findings of Zeller et al. (2005) that OLS is less able to predict the poverty incidence when the actual headcount is relatively low.

That one-step OLS of Model 2 provided the best overall accuracy is only true if we use the BPAC as benchmark. The best poverty accuracy was achieved using two-step quantile regression. Even if one-step OLS of Model 2 is providing the best BPAC, the poverty accuracy with this method is comparatively low (44.4% in 2005 and 54.7% in 2007). Nevertheless, the predicted poverty headcount with this method was 19.5%, which is very close to the actual headcount of 18.79%. We can state that none of the models had big advantages regarding the robustness if we applied the 2005 indicators to the 2007 data-set.

From our findings we draw the conclusion that Model 2, which could be easily applied by local organizations for targeting, is still a good choice for poverty assessment. Even if the one-step OLS coefficients provide a better BPAC, we would recommend the use of one-step quantile coefficients because they provided a better poverty accuracy (73.53%) than one-step OLS, but the leakage is not as high as with two-step quantile. This tool could be applied by practitioners straightforwardly.

In general one could improve the methodology using a bigger sample where an out of sample test would be possible. An out of sample test would be to split a sample randomly into two parts. One of these parts would be used for the tool calibration and the second part would be used for poverty assessment. In our case, such a test was not possible because of the limited number of observations, which makes it not possible to split the sample.

Regarding the accuracy performance of both re-estimated models we observed that the level of accuracy was approximately the same for both years. Only the performance of one-step OLS was much better in 2007 than it was in 2005 for both models. When re-estimate the models, more conform indicators from Model 2 occurred again as from Model 1. This was due to the long-term characteristics of the indicators included in Model 2. The change in the indicator composition might be due to the fact that poverty assessment, i.e. poverty prediction, is not a causal analysis of the causes of poverty.

As concluding remark we can state that the assessment of absolute poverty by means of proxy indicators is possible on a regional level even though one has to be aware of the constraint that an over-prediction of the poor might occur. Furthermore, a re-calibration of the tools from time to time seems to be necessary. To better determine the intervals of re-calibration of the PATs further research might be needed.

References

ADBI (Asian Development Bank Institute) 2009. URL: http://www.adbi.org/discussion-paper/2005/01/14/869.malnutrition.poverty.indonesia/poverty.line/

AHMED, Akher U. and Horwarth E. BOUIS, 2002, Weighing what's practical: proxy means tests for targeting food subsidies in Egypt. Food Policy 27, 519-540

AHO, Gilbert, LARIVIÈRE, S. and F. MARTIN (editors). 1998. Poverty Analysis Manual – With Applications to Benin. United Development Program, Université Nationale du Bénin, Université Laval (Canada)

ALCARAZ V., Gabriela and Manfred ZELLER, 2008. Use of household food insecurity scales for assessing poverty in Bangladesh and Uganda. Discussion paper No. 1/2008. Research in development economics and poverty. University of Hohenheim

BAULCH, Bob and Edoardo MASSET, 2002. Do monetary and non-monetary indicators tell the same story about chronic poverty? A study of Vietnam in the 1990s. Institute of Development Studies University of Sussex, Working Paper No. 17, July 2002

COLLIER, Paul and David DOLLAR, 2002. Aid allocation and poverty reduction. European Economic Review 46 (2002) 1475-1500.

DAVID, I.P. 2000. Poverty Statistics and Indicators: How often should they be measured?. Asian Development Bank URL: (http://unstats.un.org/unsd/methods/poverty/Sid%20Aug%202000%20Povnote.PDF) (14.08.05)

VAN EDIG, Xenia, 2005. Measurement of Absolute Poverty and Indicators of Poverty among Rural Households in Central Sulawesi, Indonesia. Online Ressource Staats- und Universitätsbibliothek Göttingen URL: http://webdoc.sub.gwdg.de/master/2006/vanedig/vanedig.pdf

VAN EDIG, Xenia, SCHWARZE, Stefan und Manfred ZELLER, 2007. Indicator based poverty assessment for rural Central Sulawesi. Quarterly Journal of International Agriculture Vol. 46 (2007), No.2, pp. 145-158

GROSH, Margaret E. and Judy L. BAKER, 1995. Proxy means tests for targeting social programs, LSMS Working Paper No. 118, World Bank, Washington, DC

GROSH, Margaret and Paul GLEWWE, 2000. Designing Household Survey Questionnaires for Developing Countries – Lessons from 15 years of the Living Standard Measurement Study Vol. 1, The World Bank . Washington D.C.

HUMAN DEVELOPMENT REPORTS 2007/2008. URL: http://hdrstats.undp.org/indicators/23.html (28.04.09)

IRIS CENTER 2004, USAID Project for Developing Poverty Measurement Tools, IRIS Center, Composite Survey Household Questionnaire (adapted version for Bangladesh), final Version. URL: http://www.povertytools.org/other_documents/Composite%20Survey%20Bangladesh.pdf

IRIS CENTRE. 2005. Developing Poverty Assessment Tools Project – Note on Assessment and Improvement of Tool Accuracy. URL: http://www.povertytools.org/documents/Assessing%20and%20Improving%20Accuracy.pdf

JOHANNSEN, Julia, 2006. Operational poverty targeting in Peru – Proxy means testing with non-income indicators. International Poverty Centre, UNDP, Working Paper No. 30.

JOHANNSEN, Julia, forthcoming 2009. Operational assessment of absolute poverty by proxy mean tests – the example of Peru. Dissertation University of Göttingen

JOHANNSEN, Julia and Manfred ZELLER, 2006. Operational Poverty Targeting by the Means of Proxy Indicators – The Example of Peru. Contributed paper for presentation on the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18, 2006

KOENKER, R. and HALLOCK, 2001. Quantile Regressions, Journal of economic perspectives 15, No. 4, pp: 143-156

LOK, Renata. 1995. Technical support document: Poverty – Module 1: Poverty Indicators. SEPED/BPPS; UNDP (13.09.2005) URL: http://www.undp.org/poverty/publications/tsd/tsd1/tsd1.pdf

MINOT, Nicholas, 2000. Generating Disaggregated Poverty Maps: An Application to Vietnam. World Development Vol. 28, Issue 2, February 2000, p. 319-331

OSMANI, Siddiqur R. 2003. Envolving Views on Poverty – Concept, Assessment and Strategy. Poverty and Social Development Papers. No 7. 2003 Asian Development Bank

RAVALLION, Martin. 1992. Poverty Comparison – A Guide through Methods and Concepts. LSMS Working Paper 88. The World Bank. Washington D.C.

SEN, Armatya.1999. Development as freedom, Oxford University Press, 1999.

SCHUBERT, Renate. 1994. "Armut in Entwicklungsländern – Begriff, Ausmaß, Konsequenzen. In SCHÄFER, Hans Bernd (Editor), p. 13-39, Schriften des Vereins für Socialpolitik Bd. 234. Ducker & Humboldt. Berlin

UNITED NATIONS 2008. URL: http://www.un.org/millenniumgoals/

WODON, Quentin T., 1997. Targeting the poor using ROC curves. World Development Vol. 25, Nr. 12, pp. 2083-2092

WORL BANK 2008. URL: http://indopov.org/poverty.html

WORL BANK 2009. URL: http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTPOVERTY/0,,contentMDK:20153855~menuPK:373757~pagePK:148956~piPK:216618~theSitePK:336992,00.html

ZELLER, Manfred, SHARMA; Manohar, HENRY, Carla and Cécile LAPENU. 2001. An operational tool for evaluating poverty outreach of development policies and projects. FCDN Discussion Papers No. 111. Food and Nutrition Division. International Food Policy Research Institute. Washington, D.C.

ZELLER, Manfred 2004. Review of poverty assessment tools. AMAP

ZELLER, Manfred, JOHANNSEN, Julia and Gabriela ALCARAZ V. 2005. Developing and testing poverty assessment tools: results from accuracy tests in Peru – Final Report March 2005. USAID, EGAT, and AMAP

<u>**Appendices**</u>

Appendix 1. Indicators and corresponding coefficients for the second step of two step regressions from 2005 of Model 1

Indicators	**OLS coefficients**	**Quantile coefficients**
Intercept	5.22946	-0.0028064
Age of household head	-0.0331	0.0000395
Age of household head squared	0.00036742	-0.2479853
Household size	-0,29589	0.0110731
Household size squared	0.01626	-0.0028064
Dummy: District is Sigibirumaro	0.09757	0.1757076
Dummy: District is Kulawii	0.07665	0.0812342
Dummy: District is Palolo	-0.05193	
Dummy: District is Lore Utara	-0.14092	-0.027781
Dummy: District is Pipikoro	0.01262	0.0818578
Maximum education of female household member is completed secondary level	0.21484	0.0800268
Dummy: Household member lost weight because of food scarcity	-0.2324	-0.0809422
Food expenditure share of total consumption expenditures in per-cent (from section C: summary expenditures)	-0.00475	-0.0005321
Dummy: Household eats rice mixed with maize because of food scarcity	-0.21182	-0.1111202
Age of youngest household mem-ber	-0.01189	-0.0059062
Percentage of dependents younger than 18 and older than 60 years (in relation to household size)	-0.00699	-0.0056768
Dummy: Household head works outside of agriculture	0.4878	0.5538221
Dummy: Trunk or suitcase owner-ship	0.18062	0.5538221
Total value of furniture sets owned by household	0.02239	0.0277311
Dummy: Household agrees that people in the neighbourhood are basically honest and can be trusted	-0.1719	-0.2547795
Dummy: Household borrowed money from informal market in the last three years	0.9374	0.6022479
LOG of annualised total consump-tion expenditures from composite questionnaire	0.27978	0.25574
Total value of transportation as-sets	0.08589	0.084441
Dummy: Household made a recent home improvement	0.21363	0.1821874
Dummy: Exterior walls are out of brick or stone	0.38801	0.2989028

Source: own data

Appendix 2. Indicators and corresponding coefficients for one step regressions from 2005 of Model 2

Indicators	**OLS coefficients**	**Quantile coefficients**
Intercept	10,42384	9.1573
Age of household head	-0.02092	-0.0097
Age of household head squared	0.0001815	0.0001
Household size	-0.33009	-0.2562
Household size squared	0.01557	0.0114
Dummy: District is Sigibirumaro	-0.75771	-0.2893
Dummy: District is Kulawi	-0.54191	-0.1094
Dummy: District is Palolo	-0.33009	-0.0847
Dummy: District is Lore Utara	-0.1425	0.0745
Dummy: District is Pipikoro	-0.51655	0.0705
Total number of rooms in the dwelling	0.05019	0.0612
Dummy: Metal cooking pots ownership	0.19478	0.164
Dummy: Clock or watch ownership	0.1401	0.266
Dummy: VCD player ownership	0.31491	0.3352
Dummy: Motorcycle ownership	0.20235	0.2786
Dummy: Cow ownership	0.2953	0.2953
Dummy: Household uses other cooking fuel than collected wood	0.20555	0,338
Dummy: Toilet is own pit toilet	-0.27415	-0.3285
Dummy: Main source of drinking water is water from well in residence yard	0.16186	0.0526
Dummy: Household head sleeps in bed with thin mattress out of fibres	-0.22723	-0.0965
Dummy: Household cooks in separate kitchen	-0.30423	0.1584
Dummy: Household has own or shared electricity (including generator)	0.13892	0.1584
Percentage of dependents younger than 18 and older than 60 years (in relation to household size)	-0.00326	-0.0049
Dummy: Household made a recent home improvement	0.22777	0.2112
Number of trunks and suitcases owned	0.10318	0.0551

Source: own data