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Development of Absolute Expenditure Poverty Indicators in Northern Vietnam

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Introduction

Through strong economic growth and the redistribution of agricultural land to rural households, Vietnam has made substantial progress in poverty reduction. The Vietnamese Government Decision 170 of 2005 allowed the Ministry of Labour, Invalid and Social Affair (MOLISA) to define the beneficiaries of targeted development programs at local levels and set a poverty line of 200,000 VND/capita/month to define poor households in rural areas. This poverty line has been applied for the whole period 2006-2010, but it captures only the predicted inflation of 2006. Likewise, the MOLISA method used to identify the poor is subjective as it strongly depends on the local knowledge of households. Moreover, the lists of poor households are determined by village and commune leaders who have incentives to reduce poor households by about two percentage points annually to achieve the national target program on poverty alleviation by 2010 which makes the measurement of household income unnecessary (World Bank, 2006). Therefore, the Uplands program has developed a new poverty targeting tool with easily observable indicators and lower undercoverage and leakage rates compared to the MOLISA method.

Material and methods

The study uses per-capita daily expenditures as a proxy of income. A survey of 300 households was conducted from March 2007 to January 2008 in eight communes of northern Vietnam. To capture the seasonality of agriculture production and incomes in the survey area, two expenditure survey rounds were implemented following the methodology of the Living Standard Measurement Survey of the World Bank and focus group discussions were held in each village. A new rural national poverty line was calculated and the inflation of 2007 and 2008 were determined using a monthly geometric growth rate. The new rural poverty line used in the analysis is estimated at 9,105 VND/capita/day.

Data were collected at household (*e.g.* food, housing, education) and individual levels (*e.g.* ethnicity, gender, age, family relationship) in both lowland and upland areas by local interviewers. The data gathered also captures other facets of poverty, such as area and quality of agricultural lands, water availability, economic opportunities, social and political capitals (*e.g.* trust, vulnerability and reliance to network). In addition, information on relevant infrastructure and services were provided by commune/village leaders and local officials.

Four different models were run in SAS using the MAXR technique that seeks to obtain a model with a high R-square. These included the Ordinary Least Square (OLS), the Quantile, Linear

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Probability Model (LPM), and the Probit. In total, 210 poverty indicators were used. The MAXR technique identified best 10 indicators that most accurately reflect the ‘’true’’ poverty status of each household within the survey area. The household daily per capita expenditures was used as a dependent variable in the OLS and Quantile regressions, whereas a binary variable that takes value 1 if a household is poor and 0 otherwise served a dependent variable in LPM and Probit regressions. The Quantile regression uses the set of best 10 regressors as determined by the OLS. The Probit regression which was estimated by the Maximum Likelihood Estimation uses the best 10 poverty indicators that were identified in the LPM model.

Twelve control variables were included in all regressions with the INCLUDE statement of SAS. These variables included eight dummy variables that capture agro-ecological, cultural and socio-economic differences among communes, and three household characteristics, such as household size, household size square, age of household head, which take into account the influence of important demographic factors that have been found to be powerful variables in explaining per capita daily expenditure at the household level (Zeller et al. 2005).

The following accuracy measures are used to assess the prediction power of the models developed (Table 1).

Table 1: Definition of accuracy ratios and values for accuracy measures

Accuracy ratios	Definitions
Total Accuracy	Percentage of the total sample households whose poverty status is correctly predicted by the model.
Poverty Accuracy	Households correctly predicted as poor, expressed as a percentage of the total number of poor.
Non-Poverty Accuracy	Households correctly predicted as non poor, expressed as percentage of the total number of non 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 the predicted and the actual (observed) poverty incidence, measured in percentage points.
Balanced Poverty Accuracy Criterion (BPAC)	Poverty Accuracy minus the absolute difference between undercoverage and leakage, expressed in percentage points.

Source: IRIS (2005).

In evaluating the targeting performance, Undercoverage and Leakage are considered as error of exclusion and error of inclusion respectively. The PIE indicates the precision of a tool in correctly predicting the poverty incidence in a population. Among criteria, BPAC is used as the overall criteria to judge a model's accuracy performance. Once a model with a higher positive value of BPAC is viewed as higher accuracy regarding to the correctly predicting the poverty status of households.

Results and Discussions

Following Zeller et al. (2006) who performed out-of-sample validation tests, the initial sample was divided into two random sub-samples. Two-thirds of the households were used to calibrate the model and the remaining one-third sample was used to test out-of-sample the predictive accuracy of the model. In other words, the set of indicators and their weights were applied to the validation sample to predict the household poverty status. For that reason, Table 2 below briefly summarizes the results of the estimations for the one-third sample.

Table 2: Summary of the accuracy results from four regressions

	Total accuracy	Poverty accuracy	Undercovera-ge	Leakage	PIE	BPAC
OLS						
One-third sample	0.88	0.46667	0.53333	0.26667	-0.04	0.2
Quantile (point 38)						
One-third sample	0.91	0.66667	0.33333	0.26667	-0.01	0.6
LPM						
One-third sample	0.92	0.66667	0.33333	0.2	-0.02	0.53333
Probit						
One-third sample	0.91	0.66667	0.33333	0.26667	-0.01	0.6

Source: Calculations based on survey data

Table 2 suggests that the OLS regression yields the lowest BPAC of the out-of-sample. The Quantile regression estimated at the 38th percentile and the Probit regressions yield the highest BPAC of the out-of-sample. Both models achieve the same BPAC of about 60 percentage points and a PIE of -0.01 percentage points, implying that they predict the observed poverty rate almost perfectly. Therefore, the newly designed tool is either the model based on the Quantile or the Probit regressions. Table 3 compares the targeting performance of our newly developed tools to the currently used MOLISA tool.

Table 3: Accuracy of the newly designed tool and the MOLISA method

	Poverty Accuracy	Undercoverage	Leakage	BPAC
MOLISA method	50.0	50.0	62.0	38.0
New tool (Quantile or Probit model)	66.667	33.333	26.667	60.0

Source: Calculations based on survey data

As indicated in Table 3, the poverty accuracy of the new tool is 66.67%, compared to 50% for the MOLISA tool. Furthermore, the undercoverage of MOLISA method is very high as compared to the new tool: about half of the poor were predicted as non-poor by the commune authorities. Moreover, the leakage amounts to roughly 27% when using the new tool compared to 62% for the MOLISA tool. Finally, the MOLISA method yields a low BPAC compared to the new tool.

Table 4 introduces the best 10 poverty indicators of the newly designed tool. These indicators capture the local definition of poverty and follow the SMART criteria for proxy poverty indicators: Simple, Measurable, Adapted to local specific, Robust and Timely (CIFOR, 2007). Most of these best 10 indicators appear quite easy to answer, possible to verify, simple and time-efficient. However, the other monetary indicators are quite difficult to confirm or verify such as the value of dwelling or the clothing expenditure per capita or the value of assets. With respect to the value of dwelling, non-educated poor people might find it hard to define that value. Clothing expenditure per capita would require detail data regarding to the values of purchased and self-made products in the last twelve months. However, it occupies an important position in the tools because of significant relation with the per capita daily expenditure. The difficulty of indicators demand skillful, well-trained interviewers and are strongly effected by education level and intellectual skills of the respondents and by the interview situation (Zeller et al. 2005).

Table 4: Best 10 poverty indicators used in the Quantile and Probit regressions

Quantile model	**Probit model**
Number of goats owned by household (HH)	Dummy if house entrance has no key
Ln of current value of the dwelling	Dummy if house exterior walls is made of earth
Total areas of paddy rice cultivated by HH in rainy season	Dummy if HH cooks meal in a separate kitchen
HH head is unable to work	HH head is retired
Number of people working in political organization at the commune level known by HH	HH head's main occupation is leisure
HH head can speak Kinh	HH head is widow/widower
Ln of total current value of clothing expenditure per capita per year	HH head can speak Kinh
Ln of total current value of metal cooking pots	Ln of total current value of clothing expenditure per capita per year
HH has a telephone set or not	Ln of total current value of motorcycles owned by HH
Number of motorcycles owned by HH	Dummy if HH got a loan from VBARD in 2003

Source: Calculations based on survey data

Conclusion and Outlook

The newly developed tool outperforms the method currently used by the Government of Vietnam to classify the poor and can be objectively employed by the local governments to define the beneficiaries of the targeted development programs. However, the tool developed in this paper has yet to be tested for its robustness across time and space. The new tool appears less subjective and less time consuming than the currently used MOLISA tool. We acknowledge that the results of the new tool as shown above do not take into account the political reality that commune or village heads may modify lists of poor households due to political, administrative, budgetary or other reasons. In this sense, the superiority of the newly designed tool over the currently used MOLISA tool is likely to be overestimated. During the fourth phase of the project, we plan to use a panel research design to test the newly designed tools across time and to discuss their usefulness and practicability with local and national government.

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