Identifying the Poor Using CBMS

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Outline

Why do targeting? **Types of targeting Self-Targeting** Administrative Targeting **Household Targeting** Means Test Proxy Means Test **Categorical Targeting** Geographical Other Characteristics Conclusion

Why do targeting?

Resources are limited so we want resources to go to those who need them most.





Example: Access to NFA Rice Program

Income Quintile % of HHs in the Income Quintile who were able to access

	Total	1,367	39.1
	5	87	12.4
1	4	165	23.6
	3	258	36.9
	2	375	53.6
1	State of the second	482	68.9

Magnitude

Source: CBMS Survey 2009

 Not all HHs in the lowest income quintile were able to access the program. Yet, there were households in the richest quintile who were able to benefit from the program.

Targeting

Example: Access to NFA Rice Program

	SITE	LEAKAGE RATE	EXCLUSION RATE
the state	ALL SITES	48.9	35.6
	Rural	38.8	22.8
	Urban NCR	87.8	44.6
	Urban Area		
わたの	Outside NCR Source: Authors' ca	Iculations 41.6	47.9

•48.9 % of all households who access the program are considered non-poor ■35.6 % of poor households were not able to access the program



Self-Targeting

Makes benefits available to all but involves design features intended to discourage the non-poor from claiming them while encouraging the poor to use the program

Means Test

Verified Means Test

screens applicants based on income, assets or expenditures

Example:

- If income is below the poverty threshold, then the individual is considered poor.
- At the household level, if per capita income is below the poverty threshold, then the household is considered poor.

Means Test

Verified Means Test

- How do we determine the poor?
 - Poverty and food thresholds can be used as cut-offs.

Province	Food Threshold (2006)	Poverty Threshold (2006)
Manila	11,807	20,270
Palawan	9,046	13,344
Eastern Samar	9,413	13,029
Zamboanga del Norte	9,812	14,310

Means Test

Unverified Means Test relies on self-reported income with little or no verification

Socio-economic variables are used to predict household welfare

A weighting system is adopted to combine the different variables to come up with an index

A cut-off is used to determine who are eligible or not

Why do proxy means test?

Getting accurate measures of income would require long questionnaires and trained enumerators.

Instead, proxy variables can be used to predict income.

How do we determine proxy variables?

The choice of variables are determined by economic theory and empirical evidence.
 Regression models are estimated to determine which variables can predict income well. The strategy is to find a minimum (due to cost in collecting data) set of variables that can predict income well.

How do we determine proxy variables?

Predictors of poverty status may change over time so need to use the latest available dataset, in this case the 2006 FIES. This dataset consists of 38,483 sample families.

The goodness of fit of the model is determined by how well the model is able to predict accurately the poverty status (whether poor or non-poor) of the family.

How do we determine the weights of the socio-economic variables?
No weights/equal weights
With weights
Can use econometric techniques
Multiple Linear Regression
Logistic Regression

Logit model to determine probability of being non-poor

- Can relax cut-off point to reduce exclusion rate but this increases leakage rate
 - This is a better policy option
- Can use additional filters to prune down list of eligible beneficiaries
 - For example, electricity consumption, etc.

What model to use?

- The performance of the model can be assessed by how well it is able to classify the poor and non-poor correctly, the leakage rate and the exclusion rate.
- Correctly classified the proportion of households that are correctly classified
- Leakage rate the ratio of non-poor households to the total number of beneficiaries
- Exclusion rate the ratio of poor households considered not eligible to the total number of poor households

Logistic Regression Model

 $\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \ln\left(\frac{p}{1-p}\right) = \beta X$

where: B = vector of coefficients
X = vector of independent variables
p = probability that an event occurs
(1-p) = probability that an event does not occur

Logistic Regression Model

Dependent Variable: poverty status based on per capita income

Independent Variables:

family size square of family size dependency ratio highest educational attainment of household head age of household head kind of business/occupation of household head access to electricity access to water supply access to toilet facility ownership of assets (i.e., TV, VCD/VHS/DVD, refrigerator, washing machine, airconditioner, car/jeep/motor vehicle, telephone, computer, microwave oven) urbanity region

Classification Tables

	Probability cut-off: 0.50 Frequency				
	Predicted poverty	Actual poverty status			
14	status	non-poor	poor	Total	
周	non-poor	25,824	3,400	29,225	
	poor	2,316	6,942	9,258	
1	Total	28,141	10,342	38,483	
	Percent				
	Des l'este des services	Actual poverty status			
	Predicted poverty	Actual	poverty St	aius	
	status	non-poor	poverty si poor	Total	
	status non-poor	Actual non-poor 67.11	poverty st poor 8.84	Total 75.94	
「二、二、二、二、二、二、二、二、二、二、二、二、二、二、二、二、二、二、二、	Predicted poverty status non-poor poor	Actual non-poor 67.11 6.02	poverty st poor 8.84 18.04	Total 75.94 24.06	
「一、小師」、	Predicted poverty status non-poor poor Total	Actual non-poor 67.11 6.02 73.12	poverty si poor 8.84 18.04 26.88	Total 75.94 24.06 100	
「「「「「「「「」」」」	Predicted poverty status non-poor poor Total Correctly classified:	Actual non-poor 67.11 6.02 73.12 85.14	poverty st poor 8.84 18.04 26.88	Total 75.94 24.06 100	
「「「「「「「「「」」」」	Predicted poverty status non-poor poor Total Correctly classified: Exclusion rate:	Actual non-poor 67.11 6.02 73.12 85.14 32.88	poverty st poor 8.84 18.04 26.88	Total 75.94 24.06 100	

Classification Tables

Probability cut-off: 0.70					
Frequency	Frequency				
Predicted poverty	Actual poverty status				
status	non-poor	poor	Total		
non-poor	23,424	1,771	25,195		
poor	4,716	8,571	13,288		
Total	28,141	10,342	38,483		
Percent					
Predicted poverty	Actual	tual poverty status			
status	non-poor	poor	Total		
non-poor	60.87	4.60	65.47		
poor	12.26	22.27	34.53		
Total	73.12	26.88	100.00		
Total Correctly classified:	73.12 83.14 17.12	26.88	100.00		

Classification Tables

	Probability cut-off:	0.80			
	Frequency				
	Predicted poverty	Actual poverty status			
14	status	non-poor	poor	Total	
用	non-poor	21,455	1,064	22,519	
	poor	6,685	9,278	15,964	
	Total	28,141	10,342	38,483	
	Percent				
	Due diete die enventer	Actual poverty status			
	Predicted poverty	Actual	poverty st	latus	
	status	Actual non-poor	poverty st poor	Total	
	status non-poor	Actual non-poor 55.75	poverty si poor 2.76	Total 58.52	
	Predicted poverty status non-poor poor	Actual non-poor 55.75 17.37	poverty st poor 2.76 24.11	Total 58.52 41.48	
	Predicted poverty status non-poor poor Total	Actual non-poor 55.75 17.37 73.12	poverty st poor 2.76 24.11 26.88	Total 58.52 41.48 100.00	
の一般の一般が	Predicted poverty status non-poor poor Total Correctly classified:	Actual non-poor 55.75 17.37 73.12 79.86	poverty st poor 2.76 24.11 26.88	Total 58.52 41.48 100.00	
「「いたい」へいていたいとう	Predicted poverty status non-poor poor Total Correctly classified: Exclusion rate:	Actual non-poor 55.75 17.37 73.12 79.86 10.29	poverty st poor 2.76 24.11 26.88	Total 58.52 41.48 100.00	

Results for varying probability cut-offs

Probability Cut-off	Exclusion rate	Leakage rate	Sensitivity*	Specificity**	Correctly classified
0.50	32.88%	25.02%	91.77%	67.12%	85.14%
0.55	28.65%	27.63%	89.99%	71.35%	84.98%
0.60	24.43%	29.83%	88.19%	75.57%	84.80%
0.65	20.63%	32.70%	85.83%	79.37%	84.09%
0.70	17.12%	35.49%	83.24%	82.88%	83.14%
0.75	13.57%	38.28%	80.30%	86.43%	81.94%
0.80	10.29%	41.88%	76.24%	89.71%	79.86%

- * % correctly classified non-poor
- ** % correctly classified poor

Categorical Targeting

refers to selection of broad groups of households or individuals based on a common characteristic (e.g. geographical location)

Geographical Targeting

 eligibility of benefits is determined by location of residence
 particularly appropriate in circumstances when:

considerable variations exist in living conditions across regions

administrative capacity is sufficiently limited so as to preclude use of individual or household assessment

delivery of the interventions will be a fixed site, such as school, clinic or store

Proportion of households without access to safe water supply in Agusan del Sur, by barangay



Geographical Targeting Combined with Household Assessment

combined use of multiple targeting mechanisms may lead to more accurate outcomes

Proportion of children aged 0-5 years old who are malnourished in Marinduque, by barangay



Proportion of children aged 0-5 years old who are malnourished in Marinduque, by barangay



Proportion of children aged 0-5 years old who are malnourished in Torrijos, Marinduque, by purok and location of households



Conclusion

CBMS data can be used to identify the poor. This will facilitate the implementation of targeted programs and ensure that benefits accrue to the poor.

