CHAPTER VII. POVERTY ANALYSIS FOR POLICY USE: POVERTY PROFILES AND MAPPING

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Introduction

This chapter focuses on the formulation of poverty reduction policies. It shows how various poverty tools can be of considerable value to policy makers in strengthening the poverty alleviation impact of government spending. Poverty profiles can play an important role in understanding poverty and formulating poverty reduction policies. In this chapter, we provide some country specific examples to illustrate how poverty profiles can be constructed and how they can be utilized to design policies.

The primary step in determining the degree of poverty is establishing a poverty line that specifies in monetary terms a society's judgment regarding the minimum standard of living to which everybody should be entitled. Once the poverty line is determined, one can construct poverty profiles, which provide overall estimates of poverty, distribution of poverty across sectors, geographical regions and socioeconomic groups, and a comparison of key characteristics of the poor versus non-poor.

[43]We are thankful to Fabio Soares for his helpful comments.

The method of setting the poverty line can greatly influence poverty profiles, which are the key to the formulation of poverty reduction policies. Unfortunately, setting a poverty line is not a straightforward exercise; indeed, it is often a very contentious exercise. Setting a poverty line involves many conceptual and practical problems. These are critical from the point of view of policy development, but they are often ignored due to their complexity. This matter has been dealt with in great detail in Chapters 3 and 5.

Once researchers define the poverty line, then they can calculate the number and percentage of poor in the country. These are estimates of incidence of poverty, which are obtained under the assumption that if a household is identified as poor, then all its members are also poor. These poverty estimates provide no information about the depth of poverty. One index of poverty that does take account for the depth of poverty is the poverty gap ratio. This index captures the depth of poverty by contrasting the mean income (or consumption shortfall) relative to the poverty line, averaged across the whole population[44]. Thus, this measure gives us an idea about the total resources required to bring all the poor up to the poverty line.

Finally, there is another index of poverty called the severity of poverty, which takes into account not only the depth of poverty but also inequality of income or consumption among the poor. This index helps officials focus policies on eliminating

[44] When establishing this mean, the non-poor are assigned a poverty gap of zero.

extreme or ultra poverty by giving greater weight to the income or consumption shortfalls of the very poor[45].

Geographical targeting is also becoming an important means for channeling public resources to the poor. Many governments use it to target programs, such as food aid, public works, and delivery of health care and education. This approach is commonly referred to as "poverty mapping." This chapter provides a brief review of methodology used in the construction of poverty maps. It also points out the effectiveness and limitations of poverty mapping.

7.1 Poverty monitoring and poverty profiles

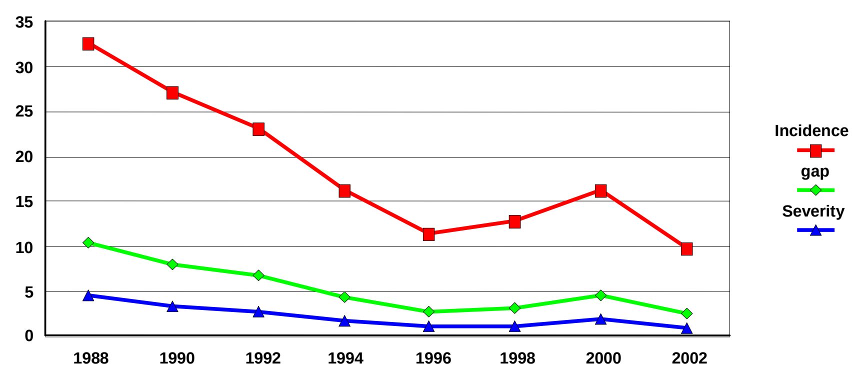
The three poverty indices discussed in the previous section are often used as a tool to monitor poverty over time at the aggregate level. Needless to say that monitoring poverty at the aggregate level is important because policy makers want to know if the government policies are helping the poor. Thailand has been monitoring poverty for more than a decade. It has a nutrition-based official poverty line, which can be used to calculate the three poverty measures. Figure 1 presents these estimates covering the period from 1988 to 2002. All three poverty measures show a parallel decline in poverty from 1988 to 1996, followed by a sharp increase through 2000 and then a sharp decrease until 2002.

[45] There is a huge range of literature on poverty measures. The most important papers among them are those by Sen (1976), Kakwani (1980), and Foster, Greer and Thorbecke (1984). The three poverty measures discussed above are the particular members of the Foster, Greer and Thorbecke's poverty measures, which are most widely used.

During Thailand's rapid growth period (1988-96), when the incidence of poverty declined very rapidly, poverty decreased at a much slower rate when measured by the poverty gap ratio and severity of poverty. This implies that the benefits of growth accruing to ultra-poor were lower than those to the poor.

During the stagnation crisis between 1996 and 2000 the headcount measure showed a much higher rate of poverty increase than the poverty gap ratio and severity of poverty index. This means that the ultra poor suffered relatively less than the poor during the crisis. During the recovery period, the ultra poor benefited relatively less than the poor.

Figure 1: Poverty in Thailand: 1988-2002



Source: Authors' calculations based on Thailand's Socio-Economic Surveys.

Poverty profiles show how poverty varies by geography and subgroups across society. Study divisions include regions, communities, sector of employment, and household size and composition. Profiles can also show how rates of economic growth in different sectors and regions affect aggregate poverty. Accordingly, poverty profiles are extremely useful in formulating the most effective economic and social policies to combat poverty. They identify regional location, employment, age, gender and other characteristics of the poor. This information can be used to formulate poverty alleviation policies. Profiles can also help answer a wide range of questions such as:

- Who are the poor?
- Where do they live?
- What do they do?
- On what sectors do they depend for their livelihood?
- Do they have access to economic infrastructure and support services such as social services and safety nets? And,
- How can the government target resources to them?

The three poverty measures--incidence of poverty, poverty gap ratio and severity of poverty--are constituents of the Foster, Greer and Thorbecke poverty indices, which have an attractive property of being additively decomposable poverty measures (see Chapter 3). This property can be quite useful in analyzing poverty profiles. For example, suppose that the population is divided into K mutually exclusive groups, and let a_k be the population share of the k^{th} group. Any FGT poverty measure, denoted by FGT_α is additively group decomposable because one can write it as:

$$\mathrm{FGT}_\alpha = \sum_{k=1}^{K} a_k \, FGT_{\alpha,k} \qquad (1)$$

where $FGT_{\alpha,k}$ is the poverty measure for the k^{th} group (Foster, Greer and Thorbecke, 1984). This implies that total poverty is a weighted average of poverty levels in all groups--the weights being proportional to the groups' share of the population.

Additively decomposable poverty measures allow one to assess the effects of changes in group poverty on total poverty. When incomes in a given group change, then group and total poverty move in the same direction. Increased poverty in a group will increase total poverty at a rate given by the group's population share a_i., The larger the population share of the group, the greater the impact will be. Equation (1) shows that $a_k FGT_{\alpha,k}$ multiplied by 100 identifies the percentage contribution of the k^{th} group to total poverty. This suggests that complete elimination of poverty within the k^{th} group would lower total poverty by this percentage. This property is desirable for evaluating anti-poverty policies.

Table 1 presents a spatial profile of poverty in Thailand in 2000. Poverty in the country varies rather dramatically by region. All three poverty measures indicate that the Northeast is the poorest region, followed by the Northern, Southern, and Central regions, and then by Bangkok. However, there is a huge regional concentration of poverty in Thailand. The Northeast region, with one-third of the country's population, accounts for more than 61 percent of the country's poor. When we measure poverty by the severity index, the contribution of Northeast to the total poverty is even higher--nearly 65 percent. This is in stark contrast with the capital region, the Bangkok metropolitan area, where the country's poverty is lowest.

Table 1: Spatial Profile of Poverty in Thailand, 2000

Regions in Thailand	Population share	Poverty incidence Index	% contribution	Poverty gap ratio Index	% contribution	Severity of poverty Index	% contribution
Bangkok	12.26	0.36	0.27	0.09	0.24	0.04	0.26
Central	22.44	5.13	7.08	1.26	6.1	0.47	5.58
Northern	18.11	18.04	20.1	4.7	18.38	1.83	17.41
Northeast	33.82	29.48	61.34	8.77	64	3.66	64.86
Southern	13.38	13.61	11.2	3.91	11.29	1.69	11.89
Whole Kingdom	100	16.25	100	4.63	100	1.91	100

Source: Authors' calculations based on Thailand's Socio-Economic Surveys.

Contribution of each region to total poverty can be used as a yardstick for allocating public assistance to each region. Since most of the poverty is found in the Northeast, government spending to reduce poverty should be concentrated in that region. There is some evidence that globalization enhances economic growth[46]. But there is no consensus about the distribution of economic growth across various socioeconomic and demographic groups. Household survey data can be used to investigate how economic growth affects poverty among various groups. This effect may be captured by the following index of poverty concentration:

$$CP = \frac{1}{2P}\sum_{k=1}^{K} a_k \mid P_k - P \mid \qquad (2)$$

where P_k and a_k are the poverty measure and population share of the k^{th} group, respectively, and P is poverty at the national level. This index will be zero if all groups

[46] See Dollar and Kraay (2000).

have same poverty. The higher the value of *CP*, the greater is the concentration of poverty. A value of 1 for *CP* implies extreme concentration of all poverty in a single group when the number of groups goes to infinity.

Table 2: Concentration of Poverty in Thailand

Period	Poverty Incidence	Poverty Gap ratio	Severity of poverty
1996	0.22	0.22	0.23
1998	0.15	0.20	0.24
2000	0.27	0.29	0.29
2002	0.26	0.26	0.27

Source: Authors' calculations based on Thailand's Socio-Economic Surveys

Table 2 shows that the concentration of poverty in Thailand declined sharply during the period between 1996 and 1998 (with exception of severity of poverty, which affects the ultra-poor more than the poor.) This is consistent with the fact that the initial impact of the 1997-98 economic crisis was most severe in Bangkok.[47] In the subsequent period of 1998-2000, the impact of the economic crisis reverberated across the country, triggering a greater increase in poverty in poorer regions. Thus, there was a huge increase in the concentration of poverty. Concentration of poverty continued to be high during the recovery period between 2000 and 2002; the country's poorer regions did not benefit from recovery as well as the richer regions.

These poverty profiles capture the regional inequities in Thailand. Division of the population into groups need not be done only in terms of geographical regions. Groups

[47] Since the Bangkok Metropolitan is the richest region, any increase in poverty in the region will reduce the concentration of poverty.

can be constructed, for example, according to gender, age, urban and rural, racial, or ethnic characteristics, and employment sector. To illustrate this point, we can look at the Philippines where groups were constructed by the work status and sectors of employment of household head. As can be seen from Table 3, the highest incidence of poverty is found among agricultural workers. Workers in industry and in trade and services suffer less than half the incidence of poverty than in agriculture. This profile suggests a need for institutional reforms, including faster land reform, more investment in infrastructure, and additional productivity improvements to increase the returns to agricultural labor.

Poverty incidence varies widely among classes of workers. Self-employed and those working in private households are more likely to be poor than other classes of labor. These findings indicate that the poor are under-represented in the formal sector, implying further that mechanisms (policies governing the welfare of workers) administered through the formal sector, such as social insurance, have a limited capacity in poverty reduction.

Table 3: Incidence of poverty by sector and class of worker in the Philippines, 1998

Sectors	Agriculture	Industry	Trade & Services	All sectors
Private households	77.6	48.7	35.3	46.9
Private establishment	59.4	25.6	20.3	31.4
Government	19.6	21.4	8.2	8.8
Self employed	63.6	40.2	23.3	51.3
Employed in own family farm or business	47.1	11.8	8.8	37.2
All classes of workers	60.5	27.9	18.9	39.2

Source: Authors' calculations based on Philippine's Annual Poverty Indicator Survey

Although poverty profiles are very useful in understanding the nature of poverty, they are limited to showing bivariate associations between various socioeconomic groups and poverty measures. In other words, they do not control for other omitted variables, which also have an impact on poverty. In many instances, this profiling approach can generate misdirected policies. To illustrate this point, it may be useful to mention Pyatt's (2000) example of Malaysia, where the data confirmed that poverty was associated with ethnicity so the main strategy of the government to reduce poverty was to redistribute wealth to Malays. However, the data also suggested a rural/urban correlation to living standards and educational attainment within the household. When all three typologies were analysed simultaneously, the ethnic dimensions were no longer significant. This suggested that ethnic differences could be explained by differences in access to educational opportunities, which significantly correspond to where people lived.

Alternatively, we may construct poverty profiles by simple transformation of logit or probit models, regressing the probability of being poor on a large number of relevant household characteristics that are generally used in poverty profiles. From these models, one can estimate the marginal effects, or elasticity, of probability of being poor with respect to any explanatory variable included in the model. The main attraction of these models is that we can isolate the effect of a single variable by controlling for all other variables included in the model.[48] Note that probit or logit models are merely descriptive from which no inference of causation can be made. Transformed coefficients should be seen as estimates of partial correlations with the probability of being poor. Still, they can

[48] As an alternative to probit or logit models, many studies use logarithm of underlying per capita income or expenditure as the dependent variable. Such a model can be statistically more efficient than the logit or probit models because it utilizes more available information on income or expenditures.

be useful in simulating alternative policies. For example, Kakwani, Soares and Son (2005) used a probit model to simulate the impact of conditional cash transfers to families with children on school attendance.

7.1.1 Capability deprivation

The income-poverty line, which identifies the poor from the non-poor, can never perfectly distinguish between individuals who are able and unable to enjoy a minimum set of capabilities (Sen 1985).[49] Thus, it is important to investigate whether the poor suffer greater capability deprivation than the non-poor. If they do, more effective policies can be devised to raise their living standards, such as providing cash or in-kind transfers or greater access to government services. This section investigates whether the poor (defined in income terms) actually suffer greater capability deprivation.

Table 4 presents indicators of educational progress among the poor and non-poor, for those between the ages of 20 and 59, living in Thailand's urban and rural areas. There is a clear link between lack of education and poverty. As of 1994, the non-poor in urban areas had an average of 6.2 years of schooling versus only 3.8 years for the urban poor. Educational attainment in rural areas was much lower, 4.0 years for the non-poor and 3.1 years for the poor. Thus, educational attainment varies substantially not only between the poor and the non-poor but also between urban and rural areas.

[49] Poverty, viewed in terms of capability deprivation, encompasses not only material deprivation (measured by income or consumption) but unemployment, ill health, lack of education, vulnerability, powerlessness, and social exclusion. Thus, this broad notion of poverty opens up to a broader range of policies that governments can follow to reduce poverty.

These gaps are even wider when one examines the percentage of the population that has completed secondary education. Only 1.3 per cent of the poor population in the age group 20-59 years had completed the secondary education in rural areas. Clearly, rural poor have a low level of educational attainment. Although the government is the major provider of education, the benefits of education are not fully flowing to the poor. These results indicate how crucial secondary education is, in both rural and urban areas, to help escape poverty.

Table 4. Educational achievements of poor and non-poor in Thailand, 1994

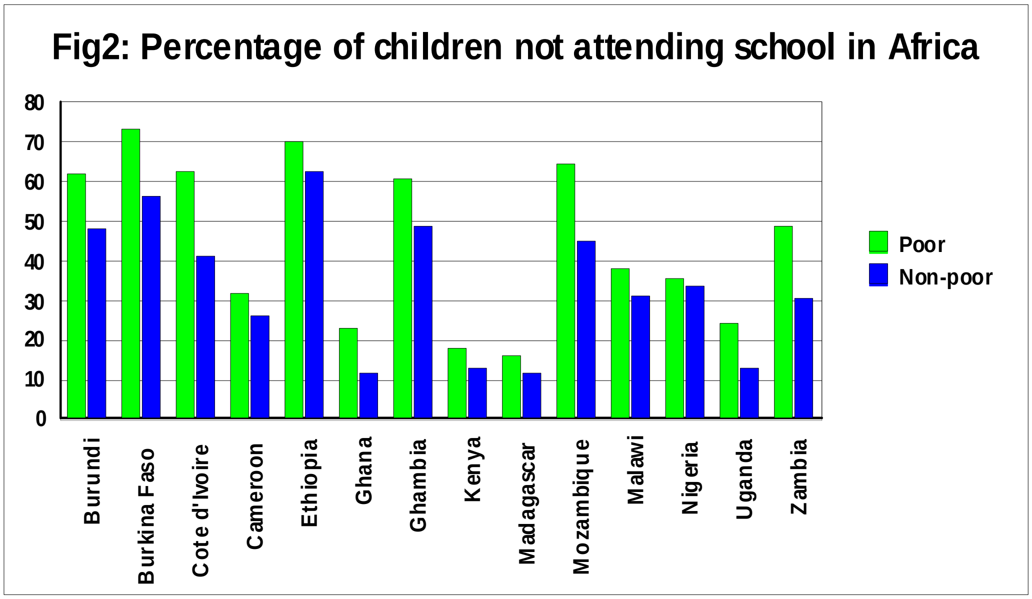
Indicators of education	**Urban areas**		**Rural areas**	
(for persons from 20 to 59 years old)	Poor	Non-poor	Poor	Non-poor
Average schooling in years	3.8	6.2	3.1	4
Percentage of literate population	71.5	78.9	64.1	73.5
Percentage with secondary education	3.3	22.0	1.3	6.2

Source: Authors' calculations based on Thailand's Socio-Economic Survey

Figure 2 shows the percentage of children, between the ages of 5 to 16 years, that are not attending school in 15 countries in Sub-Sahara Africa.[50] More than 40 percent of children (about 45 million) do not attend any type of school. Among the children living in poor families, more than 45 percent do not attend the school. The situation is extremely dismal in Burundi, Burkina Faso, Cote, d'Ivoire, Ethiopia, Ghambia, and Mozambique. The worst educational conditions for children were found in Burkina Faso where more than 70 percent of poor children do not attend school. Human capital is an important determinant of poverty. Poor children, who are unable to attend school, cannot acquire

[50] See Kakwani, Soares and Son (2005) for a detailed discussion of household income and expenditure surveys used in the construction of Figure 2.

human capital and, therefore, have little chance of escaping poverty. These results speak of the urgency for action in the Sub Sahara African countries.



Source: Kakwani,Soares, and Son (2005).

The living conditions of the poor and non-poor in Thailand are measured by a variety of indicators derived from the country's 1994 Socio-Economic Survey and delineated in Table 5.

- *Drinking Water*—This index measures the quality of drinking water--the larger the value, the cleaner is the water. Data reveals that the population living in urban areas has access to much higher quality of drinking water than households living in rural areas. The poor in each of the areas have much lower value of the index than the non-poor.

The difference in access to potable water, between the poor and the non-poor, is much larger in urban areas than in rural areas.

- *Toilet Facilities*—Sanitary human waste disposal is another important factor related to people's capability to live a healthy life. Unhygienic toilet facilities can spread infectious diseases. Such toilet facilities are also unpleasant, implying a lower standard of living. The index of toilet facilities measures quality of toilets available to a household. Toilet facility access appears not to vary significantly between the poor and the non-poor and between urban and rural areas across Thailand. This probably reflects the government's has long-term commitment to provide sewer facilities in the rural villages across the country.

Table 5. Living Conditions of the Poor and Non-poor in Thailand, 1994

	Urban areas		**Rural areas**	
Indicator of living condition	Poor	Non-poor	Poor	Non-poor
Index of drinking water	28.4	60.5	15.3	19.3
Index of water use	39.6	63.0	28.5	33.6
Toilet facility	56.8	61.5	52.2	58.0
Cooking fuel	44.5	77.5	34.5	54.8
Rooms per 100 people	48.1	71.5	46.3	65.8
Sleeping rooms per 100 people	34.8	52.0	32.4	44.4
Electricity in dwelling	96.5	99.0	89.0	94.8
Telephone in structure	2.8	32.0	1.1	3.3
Air conditioner in household	0.6	13.9	0.2	1.0
Bicycle in household	58.5	39.3	58.6	57.2
Electric Fan in household	84.2	95.5	65.6	83.9
Electric Iron in household	56.3	87.4	30.3	60.3
Motorcycle in household	42.4	49.3	31.8	56.1

Radio in household	62.1	82.8	55.1	71.0
Refrigerator in household	36.3	76.2	17.8	47.3
Color TV in household	47.7	83.0	30.4	58.0
Black and white TV in household	28.0	10.0	32.0	26.3
Video in household	4.8	34.0	1.0	7.8
Washing machine in household	4.9	28.5	0.7	6.0

Source: Authors' calculations based on Thailand's Socio-Economic Survey 1994

- *Cooking Fuel*--Gas and electricity are the cleanest and most convenient fuels for cooking. But they can be expensive, and they may not even be available in the areas where poor people live. There are many types of cooking fuel used in Thailand. The index of cooking fuel reflects its cleanliness and convenience. Empirical results show that value of index is much higher for the non-poor than the poor, especially in urban areas. Thus, non-poor households utilize much cleaner cooking fuel than poor ones.
- *Availability of Electricity*--Percentage of the population with access to electricity is very high in Thailand. About 99 percent of the non-poor population in urban areas has electricity. This figure for the urban poor is almost as high, at 96.5 percent. Even in rural areas electricity is available to 89 per cent of the poor population, which is a remarkable achievement. Thailand has clearly made enormous progress in providing electricity to almost the entire population, both poor and non-poor. Despite electricity being available in most urban and rural dwellings, the poor do not use it for cooking, indicated by the low

index value for cooking fuel. This may be due to cost of using electricity for cooking purposes.

- *Housing Condition*--SES provides data on the number of rooms (and the number of sleeping rooms) in each dwelling. The data were used to calculate the rooms (and sleeping room) available per 100 persons. This index of overcrowding shows that poor people are living in more crowded houses than non-poor people. Crowding is higher in rural areas than in urban areas. This might be surprising because urban areas, particularly Bangkok, seem so overcrowded.
- *Access to household consumer durables*--The remaining indicators in Table 5 show a wide gap between poor and non-poor access to various household consumer durables such as televisions, radios and videos. Use of telephones, air conditions, and washing machines are concentrated heavily in non-poor households located in the urban areas. For instance, in urban areas, 32 per cent of the non-poor population has an access to telephone, compared to only 2.8 per cent of the poor population. In rural areas, 3.3 of non-poor have access to phones versus 1.1 per cent of all rural poor. Similar results emerge in the case of air conditions and washing machines. Not surprisingly, poor households on average have more bicycles and black-and-white televisions than non-poor households.

The above results suggest that the poor have a much lower standard of living than the non-poor, occupying more crowded houses, with far lower access to drinking water, and ownership of fewer durable goods. And the poor are less educated. It seems from this analysis that identification of poor on the basis of income or consumption does capture to a large extent the capability deprivation aspects of poverty. This suggests that if policy focuses on increasing poor people's income, it may reduce deprivation in many other areas of capability deprivation. Alternately, governments may focus on policies and projects that would directly deal with specific kinds of deprivation, such as the lack of education or health. A more effective approach may be a combination of policies that enhance people's income and as well as reduce specific deprivations. However, from the analysis presented here, it will be difficult to make an informed judgment about specific policy prescriptions. More in depth policy analysis should be done.

7.1.2 Productive assets held by poor and non-poor

One of the important reasons why poverty persists is that the poor do not possess productive assets. And the productivity of the assets they do own may be low. This is evident from Tables 6 and 7, which review asset holdings and productivity of poor and non-poor households in China. In rural China in 1996, the per capita value of productive assets of poor households is 596 yuan versus 940 yuan for non-poor households. Poor households owned 1.6 mu of arable land compared to 2.1 mu held by the non-poor. Further, average grain production per mu was 165 for the poor households compared to 347 for non-poor households.

Table 7 shows large differences in asset holdings between the poor and non-poor households in China in 1995. These empirical results suggest that asset holdings are important determinants of household poverty status. To alleviate poverty, policies need to enhance asset holdings of the poor and increase productivity of assets held by the poor.

Table 6. Productive assets and productivity: Rural households in China, 1998

	Poor	Non-poor
Per capita productive assets (yuan)	596	940
Per capita grain production (Kilo)	406	714
Per capita housing area (square meters)	14.1	24.2
Per capita household productive expenditure (yuan)	289	668
Per capita arable land (mu)*	1.6	2.1
Average grain production per mu	165	347

* 1mu=1/6 acre

Source: Monitoring Report of China's Rural Poverty (NSB 2000).

Table 7. Productive assets and debt: Urban households in China, 1995

	Poor	Non-poor
Productive fixed assets	89.85	154.08
Financial assets	1080.46	3979.98
Housing	2784.62	5366.65
Other assets	202.8	583.35
Debt	210.59	263.36

Source: Zhao, Li and Riskin, 1999.

Many developing countries use microcredit to help the poor acquire productive assets. There are many other policy options, such as marketing training to help the poor get better prices for their produce and services. However, the more challenging issue is devising policies that would be targeted to the poor. Poverty mapping that helps identify the poor is an increasingly important tool to better target anti-poverty programs. The next section defines this technique.

7.2 Poverty mapping

Geographic targeting is becoming an important tool for allocating public resources to the poor. It is increasingly regarded as a more efficient way to reduce poverty than untargeted, universal programs. Many governments in developing countries are giving greater importance to decentralization, whereby the district or provincial government plays an important role in poverty reduction policies. To implement such policies, it is important to know the spatial distribution of poverty. Poverty mapping is the spatial analysis of poverty. It maps the incidence of poverty within each region and sub-region of a given country. A number of methods have been devised to measure spatial distribution of poverty. There is not enough space in this chapter to present all the methods that have been used in practice, so only the most widely used widely method, small-area estimation, is discussed.

Household surveys are the most important data source for measuring poverty. However, their sample sizes are too small to provide precise estimates of poverty for small geographical units, such as provinces and districts. An alternative data source are population censuses, which do not suffer from small sample problems, but typically provide very limited information from each household. For instance, censuses do not offer information on households' consumption expenditures or incomes, preventing income poverty from being measured directly. However, small-area estimation is a statistical technique that combines household survey and census data to estimate income poverty at small geographical units. It has been used by the U.S. government for planning and targeting. And recently, the World Bank staff have refined this technique and applied it to many developing countries. The technique has also been applied to Lao PDR (Kakwani (2002), a brief discussion of which is presented below.

The first step in making a small-area estimation is to formulate a model that uses regression methods to forecasts households' consumption expenditures, based on household survey data. For example, let household welfare be measured by the ratio of household consumption per capita over the per capita household poverty line (expressed in percentage terms):

$$w_i = 100\, c_i / z_i \tag{3}$$

where c_i is the i^{th} household's per capita consumption and z_i is the household's per capita poverty line. A household is poor if its welfare index in (3) is less than 100; otherwise, it's non-poor. Since the poverty line takes account of regional differences in costs of living, w_i is an index of household's real per capita consumption.[51] Each household *i* can be characterized by the row vector of X_i, which consists of *k* observable household characteristics, such as the age, sex, occupation and educational attainment of household head, household size, location of household, access to utilities, and ownership of consumer durables. Assume the welfare w_i of household *i* is generated by a stochastic model, defined as:

$$\text{Ln}\,(w_i) = \mathbf{X_i \beta} + \varepsilon_i, \tag{4}$$

[51] Note that poverty lines differ across households because of differences in regional costs of living. Thus, this model attempts to explain variations in real per capita consumption that takes account of differences in regional costs of living.

where **β** is the column vector of *k* parameters. The vector X_i consists only of variables that are found in both the household survey and the population census. The error term ε_i is the idiosyncratic shock that the household will experience in the future. Assume that ε_i normally distributed with zero mean and a variance σ_i^2 depends on observable household characteristics according to simple functional form:

$$\sigma_i^2 = X_i \delta \tag{5}$$

δ is the column vector of *k* parameters.

Suppose that $\hat{\beta}$ and $\hat{\delta}$ are the consistent estimators [estimates?] of β and δ, respectively. For large sample sizes, we can say that *Ln* (w_i) is normally distributed with mean $X_i \hat{\beta}$ and variance $X_i \hat{\delta}$, which implies that:

$$\varsigma_i = \frac{\log w_i - X_i \hat{\beta}}{\sqrt{X_i \hat{\delta}}} \tag{6}$$

is distributed as asymptotically normal with zero mean and unit variance. The probability of the i^{th} household being poor, denoted by p_i, can be written as

$$p_i = \Pr[\ w_i < 100\ ] = \Pr[\ Ln(w_i) < Ln(100)\ ] \tag{7}$$

which in view of (6) and (7) provides an estimate of p_i as:

$$\hat{p}_i = \Pr[\zeta_i < \eta_i] = \Phi(\eta_i)^{52} \tag{8}$$

where

$$\eta_i = \frac{\log(100) - X_i\hat{\beta}}{\sqrt{X_i\hat{\delta}}}$$

and Φ(.) is the cumulative density of the standard normal distribution. Thus $\Phi(\eta_i)$ is the estimated probability of a household with characteristics X_i being poor.

The objective of small-area estimation is to estimate this probability for each household in the census. Let the i^{th} household in the census be characterized by the row vector X_i^*. Then the estimated probability of this household being poor can be obtained by replacing X_i in (8) by X_i^* and is given as:

$$\hat{\hat{p}}_i^* = \Phi(\eta_i^*) \tag{9}$$

where

$$\eta_i^* = \frac{\log(100) - X_i^*\hat{\beta}}{\sqrt{X_i^*\hat{\delta}}}.$$

Equation (9) estimates the probability of being poor for each census household. It is reasonable to assume that the probability of being poor is the same for each household member. This gives the probability of being poor for every individual in the census.

[52] See Hentschel, Lanjouw, Lanjouw and Poggi, 2000.

Accordingly, we can then find the average probability of being poor for any group or regions (provinces or districts), which is an estimate of the head-count ratio for that group or region.

Suppose there are N census households in the target population, which has the total population equal to P, given by P = $\sum_{i=1}^{N} s_i$, where s_i is the size of the ith household in the census. Thus, the estimated headcount ratio for the target population is given by:

$$H = \frac{1}{P}\sum_{i=1}^{N} s_i\ \Phi(\eta_i^*) \tag{10}$$

The estimated head count ratio H given in (10) is the function of two stochastic vectors: $\hat{\beta}$ and $\hat{\delta}$. So if we know the variance and covariance matrices of these vectors, V ($\hat{\beta}$) and V ($\hat{\delta}$), respectively, then we can compute the variance of H, the square root of which gives its standard error. The derivation of the standard errors is given in the Appendix.

7.3 Some limitations in poverty mapping and alternative without census data

The most attractive feature of the technique discussed above is that it provides the standard errors of poverty estimates so that we can readily check the precision of poverty estimates. The size of the standard errors depend on two factors: (i) the explanatory power of the model estimated at the first stage from the household survey data, and (ii) the level of disaggregation sought. Empirical analysis by Hentschel, Lanjouw, Lanjouw, and Poggi (2000) shows that the precision of poverty estimates declines rapidly as the degree of disaggregation increases. Thus, one cannot achieve too much fine-tuning that might be required to achieve greater efficiency in targeting.

Household surveys generally provide information about the clusters to which the sample households belong. This information can be exploited to obtain more efficient estimators of the regression model. Elbers, Lanjouw, and Lanjouw (2001) have given a detailed discussion of the econometric issues relating to the problems of heteroskedasticity and spatial autocorrelation. These refinements will of course improve the efficiency of estimated coefficients because they do make use of all available information.

Construction of poverty maps requires having access to census data at the household level. Statistical offices of many countries do not allow, for reasons of confidentiality, such detailed information be made available to individual researchers. Some statistical authorities, however, make available aggregated census data, which unfortunately, leads to loss of precision of poverty map estimates, particularly at the lower level of disaggregation. A further requirement of poverty mapping is that the household surveys have a large subset of variables that are also in census, which may not always be the case. Variables that are available in both household survey and census may not be sufficiently correlated with the household consumption. In this case, the regression model will not be able to predict poverty maps accurately. Finally, poverty mapping assumes that the explanatory variables X in the household survey are produced from the same data-generating process as the census data. This assumption, however, can be statistically tested. The minimum requirement for this assumption to hold is that both household and census surveys should correspond to the same period. The maximum allowable time difference will depend on the rate of economic change that is taking place in the country. Many countries do not have census and household surveys for the same period.

In most developing counties, the census is conducted every ten years. Household surveys, however, are conducted more frequently. The ten-year period is too infrequent, leading to the creation of poverty maps that are outdated long before the next poverty mapping exercise is undertaken. Outdated poverty maps can lead to misallocation of scarce public resources. Given so many problems in combining household survey and census, an alternative method of constructing partial poverty maps is proposed below. This approach does not require the use of census data. The approach has been applied to identify the poor districts in the Lao PDR.

Box 1: Partial Poverty Mapping in Lao PDR

There are 18 provinces in Lao PDR, each of which has many districts. The sample size can be very small at the district level, and thus the poverty estimates at the district level may not be very accurate. For the purpose of formulating a poverty reduction policy, one wants to know which districts are poor so that policymakers can target policies to them. The first task is to define a poor district. Since the poverty rate at the national level was 38.6 percent in 1997-98, it is reasonable to assume a district to be poor if more than 50 percent of its population is living in poverty. The null hypothesis is that the percentage of poor people in a district is 50 percent or less. The alternative hypothesis will obviously involve districts where more than 50 percent of the population is poor. Thus, one can identify a district as poor if one rejects the null hypothesis at the 5 percent significance level.

If p_i is an estimate of the percentage of poor in the ith district based on a sample of size n_i, then its standard error under the null hypothesis will be $100 \times \sqrt{\frac{0.5 \times 0.5}{n_i}}$. Using a one-tailed test, the hypothesis will be rejected at the 5 percent significance level if :

$$p_i > 50 + 1.67 \times 100 \times \sqrt{\frac{0.5 \times 0.5}{n_i}}$$

If on the basis of a district sample one rejects the null hypothesis using this decision rule, the probability will be less than 0.05 that the district will be non-poor. Alternatively, if a district is identified as poor, then it will be poor with more than a 95 percent probability. This procedure helps policymakers to accurately identify a poor district. However, there is one problem with this approach. If for a district the null hypothesis is not rejected, it does not imply that the district will always be non-poor. This situation can occur when the sample for that district is very small. This is one reason to call this as a partial approach.

Empirical estimates show that of 18 provinces, the null hypothesis was rejected for 3 provinces and 128 districts; the hypothesis of being non-poor was rejected for 28 districts. Thus this partial approach found that there are 28 districts for which over 50 percent of the population is poor. The main drawback of the approach is that one cannot conclude how many districts are poor or non-poor in the remaining 100 districts.

7.4 Practical issues of implementing geographical targeting

Geographical targeting can be an effective means of channeling public resources to the poor if there is a large concentration of poverty by regions. The basic idea of geographical targeting is that the government runs the program only in the poorest regions. If the incidence of poverty is distributed uniformly across the regions, geographical targeting will not be very effective in reducing the national poverty. There will be a large reduction in poverty in the targeted regions. In untargeted regions, a large proportion of the poor will be completely left out. Thus, there will be large under-coverage rates.

The Philippines is one of the most diverse countries in the world, making it a revealing test of geographical targeting's efficacy. The country can be divided into 16 regions. The second and third columns in Table 8 provide the population shares and poverty rates in each region. The largest region is the National Capital Region (NCR) with a population share of 14.21 percent. This is also the country's least poor region, with only 11.32 percent of its population considered poor. In contrast, Bicol, Caraga, and

ARMM are among the country's poorest regions, with 54.06, 55.43, and 56.71 percent of their respective populations deemed poor.

Suppose the Philippines government has a budget of 26 billion pesos to spend on poverty alleviation in the country. If it spends all this money on a universal program, then every citizen in the Philippines will receive 30 pesos per month. Consequently, 5.09 percentage of the total population will escape poverty. Table 5's column 4 shows the degree in which a universal program effects poverty reduction from one region to another. The largest percentage reduction would occur in the country's richest region of NCR. Although the ARMM is the poorest region, poverty reduction achieved would only be 3.58 percent. Since poverty is very deep in this region, the percentage of poor that would cross the poverty line as a result of universal assistance would be small. The story, however, changes if the poverty gap and severity of poverty indices are used to assess the effectiveness of the program by region.

Table 8. Geographical targeting in the Philippines, 1998

Regions	Population shares	% of poor	% reduction in poverty: Universal program	% reduction in poverty: Targeted program
Ilocos region	5.46	38.68	4.51	5.25
Cagayan Valley	3.88	38.97	7.25	4.10
Central Luzan	10.25	20.98	7.20	3.42
Southern Luzan	13.38	24.95	5.51	4.07
Bicol region	7.04	54.06	5.20	8.32
Western Visayas	8.50	43.69	6.83	7.98
Central Visayas	7.28	50.16	3.23	6.04
Eastern Visayas	5.09	49.75	4.64	6.81
Western Mindanao	3.94	52.41	4.00	5.63

Northern Mindanao	3.88	47.63	4.58	5.03
Southern Mindanao	6.28	44.37	5.15	6.39
Central Mindanao	3.28	49.86	4.08	4.45
NCR	14.21	11.32	8.55	2.30
CAR	1.89	39.49	2.86	2.03
ARMM	2.80	56.71	3.58	4.33
Caraga	2.84	55.43	2.75	4.29
Philippines	100.00	36.67	5.09	

Source: Authors' calculations based on Philippines Annual Poverty Indicator Survey

Assume the government targets the same amount of money (26 billion pesos) into specific regions, instead of dispensing it uniformly across the country. To assess this impact, we would need to perform distinct regional calculations (see 5th column). It can be seen that if we spend all 26 billion pesos in Bicol region, the national poverty would decline by 8.32 percent, whereas untargeted universal program with the same resources could reduce the national poverty by 5.09 percent. Thus, compared to untargeted programs, geographical targeting is more effective. Moreover, geographical targeting can be further improved if it is combined with means testing within the targeted regions. The percentage reduction in poverty will be 4.33 percent if the entire money is spent in ARMM region. Because of this minimum level of improvement, the poorest region may not be targeted for the poverty alleviation. Thus, many poor persons would be left out of the program.

To achieve the greatest gains from geographical targeting, we need to fine-tune targeting to smaller geographical units--such as municipalities and districts over states and provinces. As noted, the precision of poverty estimates declines rapidly as the degree of disaggregation increases. Thus, such fine tuning may be hard to achieve. Prior to targeting a region, policy makers also need to have a clear idea about which poverty measure they are attempting to reduce. It is obvious that targeted regions should deliver a maximum reduction in national poverty. If the poverty gap is used as a poverty measure instead of the headcount ratio, the region or regions that would be selected would be different. The principle of horizontal equity requires that those gauged to be poor should receive the same benefits from the government programs. Geographical targeting requires that only those regions that can generate the largest reduction in national poverty should be selected. This means that the poor persons in regions not selected will not receive any benefits from the government programs.

To satisfy the principle of horizontal equity, one should use perfect targeting when the poor get all the benefits in proportion to the income shortfall from the poverty line (Kakwani and Son 2005). However, in practice, it is not possible to attain perfect targeting because it is difficult to accurately determine people's income or consumption. Accordingly, we generally resort to proxy targeting, such as by geographical regions or other socioeconomic characteristics of households. This leads to a violation of horizontal equity. Thus, there is a clear-cut need for further research on targeting so that there is a minimum violation of the principle of horizontal equity.

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Appendix

To calculate the standard errors mentioned in Section 6, we first need to find the variance of $\Phi(\eta_i^*)$ for each census household, which is given by

$$V(\Phi(\eta_i^*)) = [\frac{\partial\Phi}{\partial\beta}]' \, V(\hat{\beta})[\frac{\partial\Phi}{\partial\beta}] + [\frac{\partial\Phi}{\partial\delta}]' \, V(\hat{\delta}) \, [\frac{\partial\Phi}{\partial\delta}] + [\frac{\partial\Phi}{\partial\beta}]' \, \mathrm{Cov}\,(\hat{\beta},\hat{\delta})[\frac{\partial\Phi}{\partial\delta}]$$

(A-1)

where Cov $(\hat{\beta},\hat{\delta})$ is the covariance between $\hat{\beta}$ and $\hat{\delta}$, which can be shown to be equal to zero. Thus, the third term in the right hand side of (A-1) will be zero. One can also show that:

$$\frac{\partial\Phi}{\partial\delta} = -\frac{\phi(\eta_i^*)X_i^{'*}}{\sqrt{X_i^*\hat{\delta}}} \quad \text{and} \quad \frac{\partial\Phi}{\partial\delta}\,\frac{\partial\Phi}{\partial\delta} = -\frac{\phi(\eta_i^*)\eta_i^* X_i^{'*}}{\sqrt{X_i^*\hat{\delta}}} \qquad \text{(A-2)}$$

where $\phi(\eta_i^*)$ is the standard normal density function. Inserting into (A-1) gives

$$V(\Phi(\eta_i^*)) = \frac{(\phi(\eta_i^*))^2}{X_i^*\hat{\delta}} \; [X_i^* V(\hat{\beta}) X_i^{'*} + \eta_i^{*2} \; X_i^* V(\hat{\delta}) X_i^{'*}] \qquad \text{(A-3)}$$

This gives the variance of the estimated head count ratio defined in (A-1) as

$$V(H) = \frac{1}{P^2}\sum_{i=1}^{N} m_i^2 \; V(\Phi(\eta_i^*)) \qquad \text{(A-4)}$$

the square root of which provides the standard error of the estimated head count ratio for the target population.