# Describing Poverty: Poverty Profiles

## Summary

A poverty profile sets out the major facts on poverty and examines the pattern of poverty to see how it varies by

- Geography (region, urban or rural, mountain or plain, and so on)
- Community characteristics (for example, villages with and without a school)
- Household and individual characteristics (for example, educational level).

A well-presented poverty profile can be immensely useful in assessing how economic change is likely to affect aggregate poverty, even though the profile typically just uses basic techniques such as tables and graphs.

Some tables show the poverty rate for each group, for example, by level of education of household head, or by region of the country. It is good practice to show the confidence intervals of the poverty rates, which works especially well when the information is shown graphically. Alternatively, one may show what fraction of the poor have access to facilities (running water or electricity, for instance) or live in a given region, and compare this with the circumstances of the nonpoor. This chapter illustrates these concepts using a number of graphs and tables based on data from Cambodia and Indonesia.

The World Bank's *Poverty Reduction Handbook* (1992) has a long list of questions that a poverty profile should address. Provided the data are available, it is helpful to show how poverty has evolved over time. The change can often be linked to economic growth, and sometimes to specific government policies.

Most household surveys do not sample enough households to allow the analyst to break down the results at the subregional level. Yet, poverty targeting—building roads, providing grants to poor villages, and the like—typically requires such detail. One solution is to use poverty mapping: use the survey data to relate a household's poverty econometrically to a set of variables that are also available from the census; then apply the estimated regression equation to the census data to estimate whether a household is poor. This information can then be aggregated to give poverty rates for small areas.

A poverty profile is descriptive, but it serves as the basis for the analysis of poverty.

## Learning Objectives

After completing the chapter on *Describing Poverty: Poverty Profiles*, you should be able to

1. Explain what a poverty profile is and why it is useful.
2. Design tables and graphs that clearly and effectively show the dimensions of poverty.
3. Show why the use of additive poverty measures, such as the Foster-Greer-Thorbecke class of measures (see chapter 4), can facilitate poverty comparisons.
4. Explain why, in making poverty comparisons over time, one must correct for differences in sampling frame and method, adjust for price differences, and ensure comparability in the measures of income or expenditure.
5. Compute the relative risk of being poor for different household groups.
6. Summarize the steps required to undertake a poverty mapping, and explain why such a mapping has practical value.

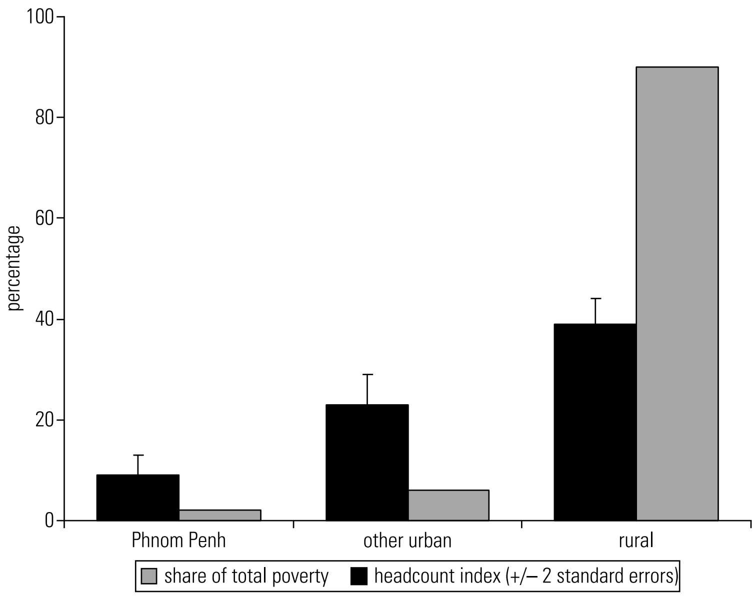
## Introduction: What Is a Country Poverty Profile?

A country poverty profile sets out the major facts on poverty (and typically, inequality), and then examines the pattern of poverty to see how it varies by geography (by region, urban or rural, mountain or plain, and so on), by community characteristics (for example, in communities with and without a school), and by household characteristics (for example, by education of household head or by household size). Hence, a poverty profile is a comprehensive poverty comparison, showing how poverty varies across subgroups of society. A well-presented poverty profile can be immensely informative and extremely useful in assessing how the sectoral or regional pattern of economic change is likely to affect aggregate poverty, even though it typically uses basic techniques such as tables and graphs.

As an example, regional poverty comparisons are important for targeting development programs to poorer areas. A study of poverty in Cambodia showed that headcount poverty rates were highest in the rural sector and lowest in Phnom Penh in 1999. Figure 7.1 shows that approximately 40 percent of the rural population, 10 percent of the population of Phnom Penh, and 25 percent of other urban residents lived in households below the poverty line. Figure 7.1 also shows the 95 percent confidence interval that surrounds the estimates of the headcount index for each area. We interpret these confidence intervals to mean that we are 95 percent certain that they embrace the true poverty. They reflect sampling error; other things being equal, the larger the sample, the narrower the confidence interval.

These standard error bands can be especially helpful when the subpopulations include only a small number of observations, because the bar charts may otherwise give a misleading sense of confidence in the precision of the illustrated poverty comparison. In the Cambodian case, the sampling errors are sufficiently small to have full confidence in the conclusion that headcount poverty rates are lower in Phnom Penh than in other urban areas, which in turn are lower than in rural areas. As for

**Figure 7.1 Headcount Poverty by Region, Cambodia, 1999**




*Source:* Gibson 1999.

contribution to the total amount of poverty, 91 percent of people living below the poverty line live in rural areas, 7 percent live in other urban areas, and 2 percent live in Phnom Penh, as the shaded bars in figure 7.1 show.

For the next example, table 7.1 presents information on Ecuadoran households' access to services. The table shows, for instance, that 52 percent of the nonpoor have waste collection, compared with just 24 percent of poor households. On average, the poor have lower access to services. An interesting finding, however, is that *within* urban areas, the poor have almost as much access to electricity as the nonpoor; in this case, essentially all the differential between the poor and the nonpoor occurs in rural areas. Note that we have rounded the figures to the nearest percentage point to avoid giving an impression of spurious accuracy.

In a further illustration, table 7.2 shows poverty measures by household characteristics—gender and education level of household head—for Malawi in 1997–98. Clearly, the higher the education level that household heads achieve, the less likely that the household is poor. This is a standard finding, but tables such as table 7.2 help quantify the size of the effect.

**Table 7.1 Selected Characteristics of the Poor in Ecuador, 1994**

| | Percentage with access to basic services | | | | | |
|---|---|---|---|---|---|---|
| | Urban | | Rural | | Total | |
| Service | Poor | Nonpoor | Poor | Nonpoor | Poor | Nonpoor |
| Sewerage connection | 57 | 83 | 12 | 28 | 30 | 64 |
| Electricity supply | 98 | 100 | 62 | 76 | 76 | 91 |
| Water from public network | 61 | 79 | 18 | 23 | 35 | 59 |
| Waste collection | 60 | 77 | 1 | 6 | 24 | 52 |

*Source:* World Bank 1996.

**Table 7.2 Poverty among Household Groups in Malawi, 1997–98**

| Household characteristics | Headcount ($P_0$) (percent) | Poverty gap ($P_1$) (percent) | Squared poverty gap ($P_2$)(× 100) |
|---|---|---|---|
| **Gender of head** | | | |
| Male | 58 | 22 | 11 |
| Female | 66 | 28 | 15 |
| **Education levels of head** | | | |
| No education | 71 | 31 | 17 |
| Less than standard IV | 63 | 25 | 13 |
| Standard IV | 58 | 22 | 11 |
| Primary school | 47 | 15 | 6 |
| Secondary school | 30 | 8 | 3 |
| University | 16 | 7 | 4 |

*Source:* Malawi National Economic Council 2000.

*Note:* Standard IV is the fourth year of primary school. Primary education follows an eight-year cycle, followed by four years of secondary school.

The World Bank's *Poverty Reduction Handbook* (1992) sets out some key questions that one may ask when preparing a poverty profile:

1. Does poverty vary widely between different areas in the country?
2. Are the most populated areas also the areas where most of the poor live?
3. How is income poverty correlated with gender, age, urban and rural, racial or ethnic characteristics?
4. What are the main sources of income for the poor?
5. On what sectors do the poor depend for their livelihoods?
6. What products or services—tradables and nontradables—do the poor sell? A tradable good is one that is, or easily might be, imported or exported. The prices of such goods are influenced by changes in the world price and the exchange rate.
7. To what extent are the rural poor engaged in agriculture? In off-farm employment?
8. How large a factor is unemployment? Underemployment?
9. What are the important goods in the consumption basket of the poor? How large are the shares of tradables and nontradables?
10. How is income poverty linked to malnutrition or educational outcomes?
11. What are the fertility characteristics of the poor?
12. To what public services do the poor have access? What is the quality of these services?
13. How important are private costs of education and health for the poor?
14. Can the poor access formal or informal credit markets?
15. What assets—land, housing, and financial—do the poor own? Do property rights over such assets exist?
16. How secure is their access to, and tenure over, natural resources?
17. Is environmental degradation linked to poverty?
18. How variable are the incomes of the poor? What risks do they face?
19. Are certain population groups in society at a higher risk of being poor than others? Households that are at high risk of being poor, but are not necessarily poor now, are considered to be vulnerable (see chapter 12 for more details about vulnerability).

A poverty profile that presents, in clear and readable form, answers to the above questions would be helpful. But the extent to which a detailed poverty profile can be constructed depends on what data are available. While certain variables, such as educational and health indicators and access to essential services, are the most basic components of a poverty profile, the relevance of many other variables depends on country circumstances. The general rule is that all variables that correlate with poverty and are relevant for policies under consideration should be included. By this rule, income-generating activities, asset positions, access to social and infrastructure services, and the composition of consumption are all of interest. Sometimes it is also helpful to compare monetary with nonmonetary measures of poverty, such as the link between per capita consumption and malnutrition.

## Additive Poverty Measures

It is much easier to make poverty comparisons using an additive poverty measure, where poverty in different areas can be added up easily to get the overall poverty rate. The Foster-Greer-Thorbecke poverty measures ($P_\alpha$ see equation (4.6) of chapter 4) may be decomposed into the poverty rates by area. To see how this works, suppose the population can be divided into $m$ mutually exclusive subgroups. Then a poverty profile presents poverty measures, $P_{\alpha,j}$, for $j = 1, \ldots, m$. Aggregate poverty can then be written as the population-weighted average of these subgroup poverty measures:

$$P_\alpha = \frac{1}{N}\sum_{j=1}^{m} P_{\alpha,j} N_j , \tag{7.1}$$

where

$$P_{\alpha,j} = \frac{1}{N_j}\sum_{i=1}^{N_j} p_\alpha(z_j, y_i^j) \tag{7.2}$$

is the poverty measure for subgroup $j$ with population $N_j$. Here $y_i^j$ is the welfare indicator of individual $i$ who belongs to subgroup $j$, where $i = 1, \ldots, N_j$. The total population $N$ is equal to $\sum_{j=1}^{m} N_j$.

An attractive feature of additive poverty measures is that they ensure "subgroup consistency." If poverty rises in any subgroup of the population, aggregate poverty will also increase, other things being equal. This makes good common sense.

## Profile Presentation

There are two main ways of presenting a poverty profile. The first splits the sample by some characteristic—for instance, region of residence, or age of household head—then shows the poverty rate for each component, as in table 7.2. The second divides up the sample by poverty status (for example, poor vs. nonpoor, or by expenditure per capita quintile), then summarizes the incidence of characteristics, such as educational level, or access to piped water, for each group, as in the shaded columns in figure 7.1.

Both methods of presentation are useful, but their value also depends on the use to which they will be put. Suppose the government wants to provide cash grants to the poor, but in practice cannot identify which households are poor, and so plans to give grants only to those living in chosen target regions (indicator targeting). In this case, we would like to know which regions have the highest incidence of poverty—which we learn from the first type of profile—to minimize the amount of grants that end up in the hands of the nonpoor.

## Poverty Comparisons over Time

If two or more rounds of household surveys are available, one may be able to measure the evolution of poverty over time. Ideally, such a measurement would use data from highly comparable questionnaires that use a similar sampling frame and research protocol and the same definitions of income or consumption.

One of the most difficult adjustments that has to be made when comparing monetary measures over time is for inflation. Deaton (2001) shows that the drop in the official poverty rate in India between 1993–94 and 1999–2000 was understated because the statistics office overstated inflation, and so raised the poverty line too quickly over time; we return to this case in more detail in chapter 16. If we have constructed a poverty line in the base year using the cost of basic needs approach, we just need to adjust this poverty line over time by applying the changes over time in the costs of each component of the poverty line (food, and nonfood items, typically).We can then compute the poverty rate in the second period. In practice, we might want to do this for each main region of the country, to take regional price variations into account. Alternatively, we could deflate income or expenditure from the second period and compare it with the original poverty line.

In practice, the lack of good price data, especially broken down by region over time, is a serious problem; indeed, it is the Achilles heel of intertemporal poverty comparisons. However, it is not the only problem, because household survey questionnaires tend to evolve. Such changes may adapt the surveys to better reflect the standard of living at a given time, but it makes intertemporal comparability more difficult.

But the demand for poverty comparisons over time is high, by governments, nongovernmental organizations, and others. So even if the comparisons are less than ideal, they are made nonetheless. In such cases, the analyst needs to be sure to

- Correct for major differences in the sampling frame and sampling method for the different surveys or the different rounds of a panel survey
- Use regional and temporal price indexes to ensure a similar definition of the poverty line over time and across regions (or to measure "real" income or expenditure over time)
- Adjust the definition of consumption or income aggregates over time to ensure that a similar definition is used. As noted in chapter 2, a significant problem is that more detailed questions about income or expenditure tend to yield higher values for overall income or expenditure.

To illustrate the construction and presentation of poverty rates over time, we again turn to the case of the Cambodian Socio-Economic Surveys of 1993/94 and 1997 (Gibson 1999). Table 7.3 compares the baseline poverty profile for Cambodia derived between these years. Note that the nominal value of the poverty line (consisting of the food poverty line plus a nonfood allowance equal to the level of nonfood consumption of persons whose per capita consumption just equals the food poverty line) increased by 15 percent in Phnom Penh, 11 percent in other urban areas, and 8 percent in rural areas.

The estimates in table 7.3 indicate that the incidence of poverty declined modestly in Cambodia as a whole (from 39 percent to 36 percent) during the period 1993/94 to June 1997. On a regional basis, poverty declined significantly in other urban areas (from 37 percent to 30 percent), modestly in rural areas (from 43 percent to 40 percent) and not at all in Phnom Penh (where it remained at 11 percent). During the same period, the estimates indicate that two other measures of poverty

**Table 7.3 Poverty Measures for Cambodia, 1993/94 and June 1997**

| | Headcount index ($P_0$) (percent) | | Poverty gap index ($P_1$) (percent) | | Poverty severity index ($P_2$), $\times$ 100 | | Memo: Poverty line (riels/day) | |
|---|---|---|---|---|---|---|---|---|
| | 1993/94 | 1997 | 1993/94 | 1997 | 1993/94 | 1997 | 1993/94 | 1997 |
| **Food poverty line** | | | | | | | | |
| Phnom Penh | 6.2 | 3.4 | 1.3 | 0.5 | 0.4 | 0.1 | 1,578 | 1,819 |
| Other urban | 19.6 | 15.4 | 4.4 | 3.3 | 1.4 | 1.1 | 1,264 | 1,407 |
| Rural | 21.9 | 20.0 | 4.0 | 3.9 | 1.1 | 1.2 | 1,117 | 1,210 |
| Total | 20.0 | 17.9 | 3.7 | 3.5 | 1.1 | 1.1 | | |
| **Poverty line** | | | | | | | | |
| Phnom Penh | 11.4 | 11.1 | 3.1 | 2.2 | 1.2 | 0.6 | | |
| Other urban | 36.6 | 29.9 | 9.6 | 7.5 | 3.6 | 2.7 | | |
| Rural | 43.1 | 40.1 | 10.0 | 9.7 | 3.3 | 3.4 | | |
| Total | 39.0 | 36.1 | 9.2 | 8.7 | 3.1 | 3.1 | | |

*Source:* Gibson 1999.

*Note:* The official exchange rate was close to 2,500 riels/$ in 1993/94 and 3,000 riels/$ in 1997.

(the poverty gap and the poverty severity index) declined significantly, both in Phnom Penh and in other urban areas but not in rural areas.

Poverty measures are sometimes translated into the *relative risks* of being poor for different household groups. These risks indicate whether the members of a given group are poor in relation to the corresponding probability for all other households in society. So, for example, if the headcount poverty rate is 20 percent nationally, but 30 percent for rural households, then rural households are 50 percent more likely to be poor than the average household.

This concept can be applied to examine whether, over time, the relative poverty risk of specific population groups decreases or increases. Table 7.4 compares the relative poverty risk of various groups in Peru in 1994 and 1997. It shows, for instance, that households with seven persons or more were 71 percent more likely to be poor in 1994 than other households in society; and that this relative risk was 106 percent in 1997 (that is, they were more than twice as likely to be poor as other households in Peru). Or again, between 1994 and 1997, the relative risk of being poor for households where the spouse of the head was working diminished (from –11 percent to –21 percent).

**Table 7.4 Poverty Risks for Selected Groups of Households, Peru**
*(percent)*

| Household characteristic | 1994 | 1997 |
|---|---|---|
| Households using house for business purposes | –28 | –29 |
| Rural households with at least one member in off-farm employment | –24 | –23 |
| Households where spouse of head was working | –11 | –21 |
| Households without water or sanitation | 54 | 50 |
| Households without electricity | 63 | 69 |
| Households where head had less than secondary education | 73 | 72 |
| Households of seven persons or more | 71 | 106 |

*Source:* World Bank 1999.

### Review Questions

**1. A poverty profile describes the main facts on poverty and relates these to geographical, community, and household characteristics.**

- True
- False

**2. Which of the following is *not* one of the key questions that are typically addressed in a poverty profile?**

- A.How important are private costs of education for the poor?
- B. On what sectors do the poor depend for their livelihoods?
- C. How is income poverty correlated with gender, and with ethnic characteristics?
- D. How has the distribution of income changed over time?

| 3. Subgroup consistency of a poverty measure means that if an individual moves into poverty, then measured poverty will increase. |
|---|
| ○ True<br>○ False |

| 4. In table 7.4, the relative risk of poverty for households without electricity was 63 percent in 1994 and 69 percent in 1997. This means that |
|---|
| ○ A. 69 percent of poor households had no electricity in 1997.<br>○ B. Fewer poor people had electricity in 1997 than in 1994.<br>○ C. Poor households were 69 percent less likely to have electricity than nonpoor households, in 1997.<br>○ D. Households without electricity were 69 percent more likely to be poor than other households, in 1997. |

## Excerpts from Poverty Profiles for Indonesia and Cambodia

This section presents excerpts from poverty profiles for Indonesia and Cambodia. These give a flavor of the types of tables and figures that are typically constructed for poverty profiles, and that are well worth imitating.

### Indonesia

Table 7.5 gives an example of a poverty profile in which the sampled households in Indonesia's 1987 SUSENAS (National Socioeconomic Survey) have been classified into 11 groups according to their principal income source. Results are given for the three main poverty measures discussed above. The following points are noteworthy:

- In the absence of adequate information on urban versus rural prices, Ravallion and Huppi (1991) assumed an urban-rural cost-of-living differential of 10 percent. Although this appears to be a reasonable assumption, their results are sensitive to this assumption.
- The poverty measures are based on the estimated population distributions of persons ranked by household consumption per person, where each person in a given household is assumed to have the same consumption. Household-specific sampling rates have been used in estimating the distributions.
- In forming the poverty profile, households have been grouped by their stated "principal income source." Many households have more than one income source. In principle, one could form subgroups according to the various interactions of primary and secondary income sources, but this would rapidly generate an

**Table 7.5 Sectoral Poverty Profile for Indonesia, 1987**

| Principal sector of employment | Population share (percent) | Headcount index ($P_0$) (percent) | Poverty gap index ($P_1$) (percent) | Poverty severity index ($P_2$), × 100 |
|---|---|---|---|---|
| **Farming** | | | | |
| Self-employed | 41.1 | 31.1 | 6.42 | 1.97 |
| Laborer | 8.6 | 38.1 | 7.62 | 2.21 |
| **Industry** | | | | |
| Urban | 3.0 | 8.1 | 1.26 | 0.32 |
| Rural | 3.4 | 19.4 | 3.00 | 0.76 |
| **Construction** | 4.3 | 17.4 | 2.92 | 0.80 |
| **Trade** | | | | |
| Urban | 6.3 | 5.0 | 0.71 | 0.17 |
| Rural | 7.6 | 14.7 | 2.42 | 0.61 |
| **Transport** | 4.1 | 10.7 | 1.53 | 0.34 |
| **Services** | | | | |
| Urban | 7.6 | 4.2 | 0.61 | 0.14 |
| Rural | 7.3 | 11.6 | 1.84 | 0.49 |
| **Other** | 6.7 | 17.1 | 3.55 | 1.03 |
| **Total** | **100.0** | **21.7** | **4.22** | **1.24** |

*Source:* Huppi and Ravallion 1991.

unwieldy poverty profile; as a general rule, it is important to keep poverty profiles straightforward and uncluttered.

- The three measures are in close agreement on the poverty ranking of sectors. For example, the two farming subgroups are the poorest by all three measures.

Changes in the poverty profile may arise from the contributions of different subgroups to changes over time in aggregate poverty. Table 7.6 provides information on the relative contribution of various sectors to aggregate poverty alleviation in Indonesia between 1984 and 1987. These are the “intrasectoral effects,” expressed as a percentage of the reduction in aggregate poverty for each poverty measure. For instance, 11 percent of the reduction in poverty (as measured by $P_0$) between 1984 and 1987 was due to the fall in poverty among farm laborers. The table also gives the aggregate contribution of shifts in population and the interaction effects between sectoral gains and population shifts.

The drop in poverty among self-employed farmers had the largest influence on aggregate poverty reduction, and most particularly on the reduction in the severity of poverty as measured by $P_2$. About 50 percent of the reduction in the national headcount index was due to gains in this sector, while it accounted for 57 percent of the gain in $P_2$. Note that the rural farm sector’s impressive participation in the reduction of aggregate poverty is due to both significant declines in its poverty measures, and the large share of national poverty accounted for by this sector.

Furthermore, 13 percent of the decline in the national headcount index was due to population shifts between various sectors of employment, mainly because people

**Table 7.6 Sectoral Decomposition of the Change in Poverty in Indonesia, 1984–87**

| Principal sector of employment | Population share, 1984 (percent) | Contribution of sectoral change: Headcount index ($P_0$) (percent) | Poverty gap index ($P_1$) (percent) | Poverty severity index ($P_2$), × 100 |
|---|---|---|---|---|
| **Farming** | | | | |
| Self-employed | 45.0 | 49.8 | 54.6 | 57.4 |
| Laborer | 9.0 | 11.2 | 14.8 | 16.5 |
| **Industry** | | | | |
| Urban | 2.6 | 0.8 | 0.4 | 0.3 |
| Rural | 3.3 | 2.8 | 3.1 | 2.7 |
| **Construction** | 4.1 | 3.2 | 2.6 | 2.2 |
| **Trade** | | | | |
| Urban | 5.4 | 2.2 | 1.6 | 1.4 |
| Rural | 6.6 | 7.2 | 5.6 | 4.7 |
| **Transport** | 3.8 | 3.6 | 2.7 | 2.2 |
| **Services** | | | | |
| Urban | 6.5 | 1.0 | 1.0 | 0.9 |
| Rural | 5.8 | 2.9 | 2.4 | 2.0 |
| Total sector effects (including omitted sectors) | n.a. | 89.3 | 93.8 | 95.1 |
| Contribution of population shifts | n.a. | 13.2 | 10.4 | 9.4 |
| Interaction effects | n.a. | –2.6 | –4.3 | –4.5 |
| **Total** | **100.0** | **100.0** | **100.0** | **100.0** |

*Source:* Adapted from Huppi and Ravallion (1991).

*Note:* n.a. = Not applicable. Minor sectors omitted.

moved out of high-poverty into low-poverty sectors. The sectors that gained in population share were almost all urban (Huppi and Ravallion 1991), and had initially lower poverty measures. The fact that population was moving out of the rural sector, where poverty was falling faster, accounts for the negative interaction effects in table 7.6.

### Cambodia

A basic breakdown of Cambodian poverty rates by region in 1999 is given in figure 7.1. The figure shows that at least 85 percent of the poor are concentrated in rural areas. Some more detailed figures are shown in table 7.7, using data from the Cambodia Socio-Economic Survey of 1999. Data in 1999 were collected in two rounds, and table 7.7 contains estimates for each round (and the pooled sample) of the three main poverty statistics, and also reports the results from the previous surveys for comparison.

An interesting feature of these results is that there is substantial discrepancy in the poverty estimates from the two survey rounds in 1999. The headcount index is

**Table 7.7 Comparisons of Poverty Estimates from Cambodian Surveys**

| | Headcount index ($P_0$) (percent) | Poverty gap index ($P_1$) (percent) | Poverty severity index ($P_2$), × 100 |
|---|---|---|---|
| SESC 1993/94 | 39.0 | 9.2 | 3.1 |
| 1997 CSES (as adjusted by Knowles [1998]) | 36.1 | 8.7 | 3.1 |
| 1997 CSES (unadjusted) | 47.8 | 13.7 | 5.3 |
| | (1.5) | (0.7) | (0.3) |
| CSES 1999 (Round 1) | 64.4 | 23.9 | 11.3 |
| | (2.3) | (1.3) | (0.8) |
| CSES 1999 (Round 2) | 35.9 | 6.5 | 2.0 |
| | (2.4) | (0.7) | (0.4) |
| CSES 1999 (both rounds combined) | 51.1 | 15.4 | 6.7 |
| | (1.8) | (0.9) | (0.5) |

*Sources:* Gibson 1999; Knowles 1998.

*Note:* The exchange rate was close to 3,000 riels/$ in 1997 and 3,800 riels/$ in 1999. SESC = Socio-Economic Survey of Cambodia; CSES = Cambodian Socio-Economic Survey. No sampling errors (reported in parentheses for the other years) are reported by the first two poverty profiles, but the relative errors for SESC 1993/94 and the adjusted 1997 CSES would likely be higher than the relative error in 1999 because the sampling scheme used previously was not as efficient (fewer clusters and broader stratification). The poverty line used for the unadjusted 1997 CSES results takes values of 1,923 riels per person per day in Phnom Penh, 1,398 in other urban, and 1,195 in rural.

almost 30 percentage points higher for round 1 than for round 2, while the poverty gap and poverty severity indexes are between four and six times higher. These troubling differences are also large relative to the variation across previous survey estimates of poverty in Cambodia, and would need to be investigated and fully discussed in a serious poverty profile. If the discrepancies between the two survey rounds are ignored, and the data are pooled, the resulting poverty estimates are fairly similar to the unadjusted 1997 estimates, showing a slight increase in all three poverty measures (table 7.7).

The pattern of poverty with respect to the age group of the household head is reported in table 7.8, based on round 2 of the Cambodia Socio-Economic Survey of 1999. It is apparent that poverty rates rise with age, reaching a maximum for the 36- to 40-year-old group of household heads, and then decline. A similar pattern was reported in the 1997 poverty profile. Once again, the definition of headship and its economic interpretation may confound the results, so a more detailed examination would be needed before any interventions might be designed on the basis of these age patterns. For example, the household head need not be the major economic contributor to the household; respondents may simply have nominated the oldest or most senior member. Thus, the relatively low poverty rate for people living in households whose head is age 61 years and above may reflect the wealth accumulation that this elderly head has achieved, or it could be that there is a younger generation within the household whose economic success is sufficient to allow them to support their elders within the same household. As a general rule, it is wise not to put too much

**Table 7.8 Distribution of Poverty by Age and Gender of Household Head in Cambodia, 1999**

| | Headcount index ($P_0$) | | Poverty gap index ($P_1$) | | Poverty severity index ($P_2$), × 100 | | Share of total population (percent) |
|---|---|---|---|---|---|---|---|
| | Index (percent) | Contribution to total (percent) | Index (percent) | Contribution to total (percent) | Index | Contribution to total (percent) | |
| | 35.9 | 100.0 | 6.5 | 100.0 | 2.0 | 100.0 | 100.0 |
| **Age of head** | | | | | | | |
| 18–30 years | 36.7 | 10.7 | 5.6 | 9.1 | 1.4 | 7.5 | 10.5 |
| 31–35 years | 35.4 | 10.9 | 5.4 | 9.2 | 1.6 | 8.8 | 11.1 |
| 36–40 years | 43.6 | 21.2 | 8.0 | 21.6 | 2.7 | 23.3 | 17.5 |
| 41–45 years | 40.3 | 15.7 | 7.3 | 15.8 | 2.2 | 15.3 | 14.0 |
| 46–50 years | 36.5 | 14.4 | 7.7 | 16.9 | 2.4 | 16.9 | 14.2 |
| 51–60 years | 28.3 | 15.8 | 5.3 | 16.3 | 1.7 | 16.8 | 20.0 |
| 61 and above | 32.0 | 11.3 | 5.6 | 11.1 | 1.8 | 11.3 | 12.7 |
| Male | 36.4 | 84.4 | 6.6 | 84.2 | 2.1 | 85.1 | 83.3 |
| Female | 33.6 | 15.7 | 6.1 | 15.8 | 1.8 | 14.9 | 16.7 |

*Source:* Gibson 1999, based on round 2 of the CSES of 1999.

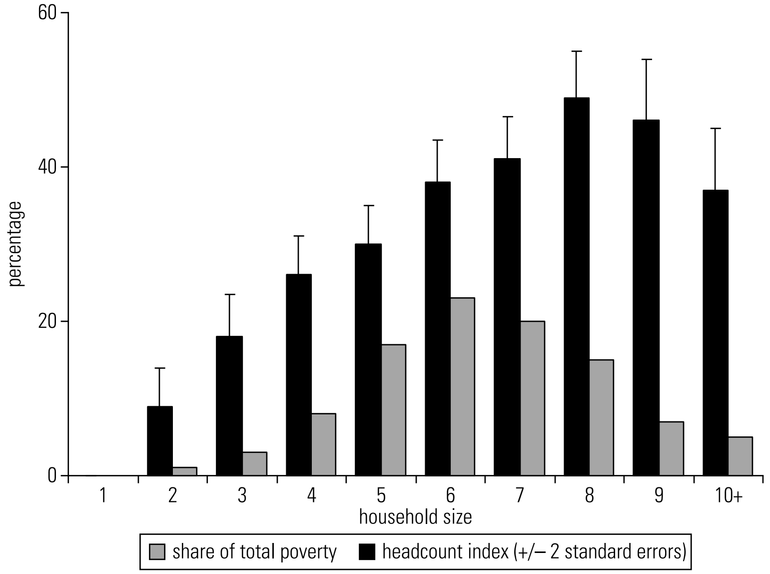
emphasis on breakdowns by household head, given the problems involved in its definition. Reflecting this, the United States Census no longer even asks who the head of the household is; it has also become less socially acceptable to identify a "head" of household in the United States.

Note that the poverty level is lower among female-headed households in Cambodia. This is not unusual in Southeast Asia. Often a finer breakdown is more helpful—for instance, households headed by widows, by married women with an absent husband (who may send remittances home), and so on.

There are two reasons why widow-headed households, and households where there has been a dissolution (that is, separation or divorce), could be at greater risk of poverty. The loss of an economically active household member, as would occur with the death of a husband in war, for example, is likely to cause a large income shock that could push a household into poverty. The second factor, and the one that links marital status with household size, is that households headed by widows tend to be smaller than average, which will constrain the effective living standards of their members if there are economies of scale in household consumption.

In Cambodia, the headcount poverty rate in 1999 increased smoothly with household size to a maximum rate for households with eight members (figure 7.2). In the round 1 data, the highest headcount poverty rate was for households with nine members. A relationship like that shown in figure 7.2 needs to be treated with caution, because it does not control for economies of scale in household consumption: large households may have lower expenditures (per capita), not because their members are poor but because they do not need to spend as much per person to reach the

**Figure 7.2 Poverty by Household Size, Cambodia, 1999**



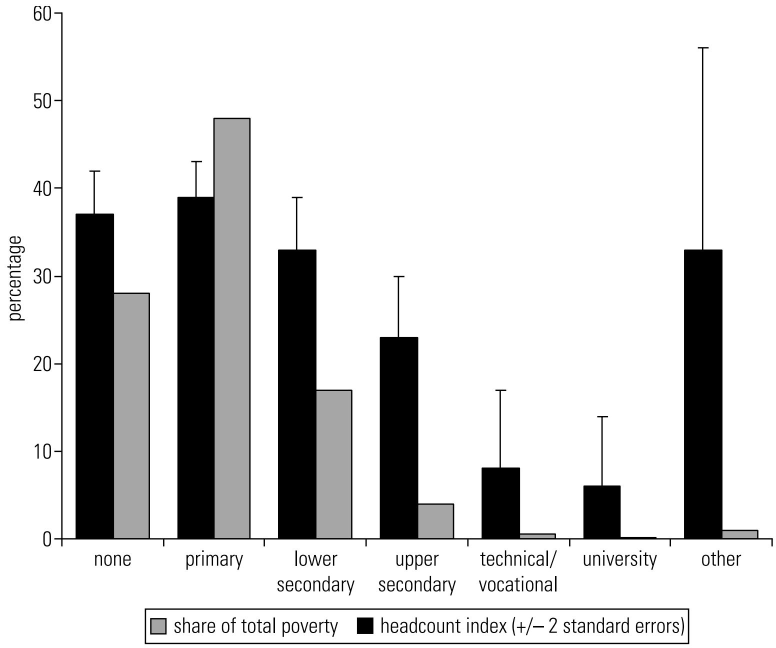

*Source:* Gibson 1999.

same standard of living. However, there is some evidence that such economies of size are relatively unimportant for Cambodian households, in which case the pattern shown by figure 7.2 may be a useful basis for identifying the poor.

Previous poverty profiles showed that poverty rates were relatively high among those whose household heads either had no schooling or had only primary schooling. Poverty rates then fall with the attainment of lower secondary education, fall farther with upper secondary, and are almost zero if the household head is a university graduate. But those whose household heads had a technical or vocational or other form of education had a higher poverty rate than those with primary schooling (at least in the 1997 poverty profile), for reasons that are not entirely clear. This is a good example of a case where the poverty profile raises questions that require further examination.

According to the survey estimates, there was little difference in 1999 in poverty rates between those whose household heads has no schooling and those whose heads has some primary education (figure 7.3). Although the survey estimate of the headcount poverty rate is slightly higher for the primary schooled group, the estimates for both groups are surrounded by wide and overlapping confidence intervals. One possible explanation for this somewhat surprising result is that primary education is of very low quality, so it adds little to one's earning ability. The finding is in line with evidence from a number of other countries that suggests that a secondary education is required to truly pull someone out of poverty.

**Figure 7.3 Poverty by Education Level of Household Head, Cambodia, 1999**




*Source:* Gibson 1999.

## Poverty Mapping

It is still unusual for living standards surveys to sample more than 10,000 households because of the high cost of administering long and complex questionnaires. A corollary is that poverty rates based on these surveys can only be disaggregated reliably to the level of a handful of broad regions. For example, the Cambodian Socio-Economic Survey of 1999 allowed one to estimate poverty for Phnom Penh, other urban areas, and rural areas, but not reliably for every district in the country.

Yet we are often interested in a more detailed poverty map that would show poverty rates for relatively small geographic units, because even within a given region there are typically wide divergences in standards of living, and hence poverty. Relatively detailed poverty maps can, in principle, improve the targeting of interventions. In designing poverty alleviation projects and allocating subsidies, resources will be used more effectively if the neediest groups can be better targeted, which both reduces the leakage of transfer payments to nonpoor persons and reduces the risk that poor persons will be missed by a program. Poverty maps can also help governments articulate their policy objectives. Basing allocation decisions on observed geographic poverty data rather than on subjective rankings of regions increases the transparency of government decision making and thus can help limit the influence of special interests in allocation decisions. There is a role for well-defined poverty maps in lending credibility to government and donor decision making.

But detailed poverty maps cannot be generated from survey data alone. The problem is that if one tries to use the survey data to measure poverty in each district, those estimates would be based on just a few observations, and so would be too imprecise to be useful. To illustrate this, suppose that we wish to measure the headcount poverty rate ($P_0$), and that our survey data give an estimated poverty rate of $\hat{P}_0 = 0.30$ with a standard deviation of $s = 0.40$. We are interested in knowing how accurate our estimated poverty rate really is. If we were to redo the survey on a new sample, our estimated poverty rate would not be quite the same, simply because of sampling error.

For reasonably large samples (above about 30 or so), we may invoke the central limit theorem to argue that the estimate of the poverty rate is approximately normally distributed, with mean $\mu$ and variance $\sigma^2/N$, where $N$ is the sample size, so $\hat{P}_0 \sim N(\mu, \sigma^2/N)$ Using estimated values for the mean and variance, we may create confidence intervals: there is a 95 percent probability that the true poverty rate is in the interval (0.289, 0.311) if the sample size is 5,000; but if we only have 30 observations—from a single cluster of households, for instance—then the 95 percent confidence interval for the poverty rate would be (0.157, 0.443). At this level of detail, the estimate of the poverty rate is too imprecise to be of any real value.

One solution is to increase the size of the sample of households surveyed. This is the approach taken by Vietnam, which has 64 provinces and cities, each of which wants its own measure of poverty (and other indicators of welfare, such as per capita expenditure)—both to evaluate the performance of provincial governments, and to help determine the size of subsidies paid by the central to the provincial authorities. The Vietnam Living Standards Survey of 1992/93 sampled 4,800 households, but the Vietnam Household Living Standards Survey of 2006 interviewed 9,189 households.

An alternative solution is to *combine the survey data with census data to create more detailed poverty maps*. Household surveys generate rich data, from which one may estimate such measures as expenditure, income, and poverty, but they cover relatively few households. Conversely, census data (and sometimes large household sample surveys) are available for all households (or very large samples of households) and can provide reliable estimates at highly disaggregated levels such as small municipalities, towns, and villages. But censuses do not contain the income or consumption information necessary to yield reliable indicators of the level and distribution of welfare such as poverty rates or inequality measures.

The basic idea is to use the detailed survey data to construct a "model" of consumption expenditure (or any other household- or individual-level indicators of well-being) as a function of variables that are common to both the household survey and the census. For example, a simple model might take the form

$$\ln(y_i) = \mathbf{X}_i'\mathbf{b} + e_i\,, \tag{7.3}$$

where $y_i$ is expenditure per capita (or some other welfare measure) for the $i$th household, and the matrix $\mathbf{X}_i$ includes variables common both to the survey and to the census, such as household size, the educational level of the household head, the proportion of the household consisting of prime-age adults, and sometimes information about the quality of housing.

The second step uses the estimates from equation 7.3, along with census data on the $X_i$ variables, to get predicted values of $y_i$ for every household in the country. These predicted values can then be used to measure poverty at a much more disaggregated level. This whole process is often referred to as small-area estimation (or "micro-level estimation").

We now need to ask how accurate these disaggregated measures are. Elbers, Lanjouw, and Lanjouw (2003) distinguish three types of error:

- *Model error*. Model error occurs because the model in equation (7.3) is not known exactly; the coefficients are estimated ($\hat{\mathbf{b}}$) and are subject to error. The importance of this source of error depends on how tightly model (7.3) fits the data.

- *Computation error*. Typically quite small, computation error is due to the need (in many cases) to use simulation techniques in the estimation process.

- *Idiosyncratic error*. This is the error that arises because we do not observe, in the census, all the characteristics of the household that are relevant when measuring welfare. This source of error becomes more important as we try to measure welfare for smaller and smaller target populations (for example, a village or ward rather than a region or country).

Elbers, Lanjouw, and Lanjouw (2003) illustrate both the uses and limits of small-area estimation using data from Ecuador. The 1994 Encuesta sobre las Condiciones de Vida[1] obtained 4,391 usable responses from households, which allowed a reasonably accurate measurement of poverty rates at the level of eight regions, but was clearly inadequate for measuring poverty at the level of each of the country's thousand parishes (*parroquias).* However, the 1990 census counted about 2 million households, and collected information on a range of demographic variables such as household size, age, education, occupation, housing quality, language, and location.

Elbers, Lanjouw, and Lanjouw (2003) fit models similar to (7.3) separately for each of the eight regions, using data from the 1994 Encuesta; they also allowed for correlation within the clusters of primary sampling units, a refinement explained more fully in their paper. They then drew groups of 100 households randomly from

**Table 7.9 Mean and Standard Error of Headcount Poverty Rate for Different Sample Sizes, Rural Costa Province, Ecuador, 1994**

| | Number of households | | | |
|---|---|---|---|---|
| | 100 | 1,000 | 15,000 | 100,000 |
| Estimated headcount poverty rate ($\hat{P}_0$) | 0.46 | 0.50 | 0.51 | 0.51 |
| Estimated standard error | 0.067 | 0.039 | 0.024 | 0.024 |

*Source:* Elbers, Lanjouw, and Lanjouw 2003.

the 1990 census data for the rural Costa region, and grouped these into units of 1,000 households, 15,000 households, and 100,000 households. The results of this experiment are shown in table 7.9, which displays the estimated headcount poverty rate, and standard error of this measure, for the different sizes of units. At the level of 100 households, the standard error of the estimate of the headcount poverty rate is 0.067. This is a large number; roughly, it implies that with 95 percent probability, the true poverty rate is in the interval 0.33 to 0.59, which is too high a level of imprecision for the results to be very useful. However, the precision at $N$ = 15,000 is essentially the same as at $N$ = 100,000, so this technique does—in Ecuador at least—allow one to measure poverty fairly reliably at the level of a medium-size town.

The gain in precision from wedding survey to census data is illustrated in table 7.10, which is based on Table II in Elbers, Lanjouw, and Lanjouw (2003). For each of the eight regions of Ecuador, column (2) shows the standard error of the estimated poverty rate, based directly on the survey data, along with the population in each region (column (3)). Elbers, Lanjouw, and Lanjouw then use small-area estimation, following the steps outlined above, to measure poverty at the parish level (or at the level of zones, in the urban provinces of Quito and Guayaquil). These are a hundred times less populous (see column (5)) than the regions, yet have roughly the same standard errors. In other words, small-area estimation allowed for a hundred times more disaggregation for a given level of reliability than the use of survey data alone would permit.

How useful is this result? Elbers, Lanjouw, and Lanjouw (2003) caution that even at the parish level in Ecuador, poverty targeting would be highly imperfect because only 15 percent of rural inequality is due to differences *between* parishes; the remaining 85 percent of rural inequality is due to inequality within parishes. Even at the local level, living standards in Ecuador are heterogeneous; thus, interventions designed to ameliorate poverty by targeting poorer parishes will

- Help many nonpoor (the more affluent residents of poor parishes)
- Leave out many poor (the poor residents in rich parishes).

Thus, even a sophisticated poverty mapping has serious limitations as a practical guide to geographic targeting.

**Table 7.10 Standard Errors of Estimates of Headcount Poverty Rates, for Survey Data and for Small-Area Estimation, Ecuador, 1994**

| | Sample data only (regions) | | Combined data (parishes, zones)/Small-area estimation | |
|---|---|---|---|---|
| Area | Standard error of estimate (2) | Population (thousands) (3) | Standard error of estimate, median (4) | Population median (thousands) (5) |
| Rural Sierra | 0.027 | 2,509 | 0.038 | 3.3 |
| Rural Costa | 0.042 | 1,985 | 0.046 | 4.6 |
| Rural Oriente | 0.054 | 298 | 0.043 | 1.2 |
| Urban Sierra | 0.026 | 1,139 | 0.026 | 10.0 |
| Urban Costa | 0.030 | 1,895 | 0.031 | 11.0 |
| Urban Oriente | 0.050 | 55 | 0.027 | 8.0 |
| Quito | 0.033 | 1,193 | 0.048 | 5.8 |
| Guayaquil | 0.027 | 1,718 | 0.039 | 6.5 |

*Source:* Elbers, Lanjouw, and Lanjouw 2003.

For a recent application to Vietnam, see Minot and Baulch (2002); discussions of the methodology may be found in Hentschel et al. (2000); Elbers, Lanjouw, and Lanjouw (2000); and Alderman et al. (2000).

## Automating Poverty Profiles: The ADePT 2.0 Program

The creation of poverty profiles requires some computer programming proficiency, and can be time consuming. In an effort to make the process easier and quicker, the World Bank has developed a package within Stata that makes it simpler to generate a number of standard tables and graphs. The package is programmed as an *.ado file, and may be installed by first opening Stata and then typing, in the command line, `net install adept, replace from(http://siteresources.worldbank.org/INT POVRES/Resources)`. To use the package one needs a computer that is working with Microsoft Windows, has Microsoft Excel, and is using version 9.2 or higher of Stata.

After the program has been installed, it suffices to type `adept` within Stata to invoke the program, which then prompts the user for, at a minimum, information on the welfare indicator of interest (for example, expenditure per capita), household ID, a binary variable that measures the urban or rural location of the household, the size of the household, and the poverty line. It allows, but does not require, the user to provide information on a number of other variables, including region and sampling weights; and it will also handle data from multiple years. The program then generates a series of tables (that it puts into an Excel file) and graphs (which are put into *.emf image files).

It took the authors less than half an hour, using ADePT, to generate 10 tables and two graphs using basic data from the Vietnam Household Living Standards Survey of 2006. To illustrate the sort of output that the program generates, two examples are provided here. Table 7.11 (which corresponds to table 3.2a in ADePT) provides three measures of inequality, both for Vietnam overall and separately for urban and rural areas, based on real expenditure per capita. It then separates inequality into that part that is due to differences between groups, and that occurring within groups. Although it depends somewhat on the measure used, about a fifth of inequality is attributable to the urban-rural divide; most inequality is within these broad areas, with more inequality within the urban than the rural areas. Figure 7.4 also provides information on the distribution of expenditure per capita for the country at large, and for urban and rural areas. The vertical lines in the figure represent the means of the respective distributions.

While the ADePT 2.0 program offers convenience, it is most useful at providing a first draft of a poverty profile. Ultimately, it is desirable to recheck all the numbers using one's own Stata commands—they may not always agree with the ADePT version—but this becomes much easier once ADePT has helped clarify what breakdowns of the data are likely to be useful.

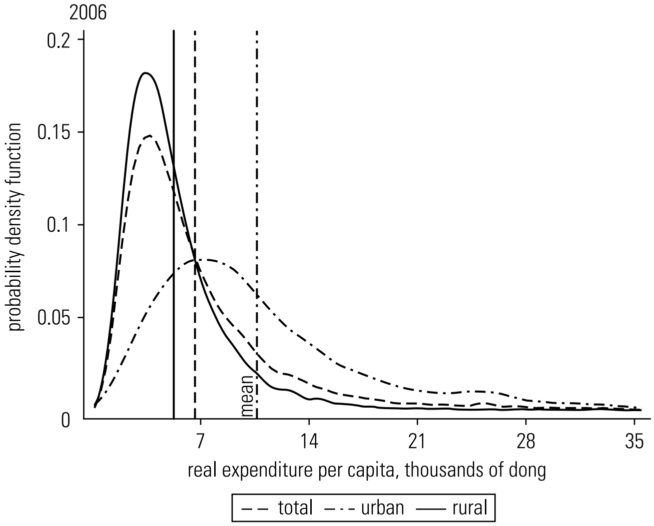
**Table 7.11 Decomposition of Inequality (in Expenditure per Capita) by Urban and Rural Areas, in Vietnam, 2006**

| Component of inequality | Theil's L index GE(0) | Theil's T index GE(1) | GE(2) |
|---|---|---|---|
| Overall inequality | | | |
| 2006 | 24.7 | 27.9 | 45.0 |
| Urban | 23.2 | 25.2 | 37.2 |
| Rural | 17.3 | 18.8 | 26.7 |
| Within-group inequality | | | |
| 2006 | 18.8 | 21.4 | 37.8 |
| Between-group inequality | | | |
| 2006 | 5.9 | 6.5 | 7.2 |
| Between-group inequality as a percentage of overall inequality | | | |
| 2006 | 24.0 | 23.2 | 16.1 |

*Source:* Table generated by ADePT 2.0 program, using data from the Vietnam Household Living Standards Survey of 2006.

*Note:* See chapter 6 for an explanation of GE(0), GE(1), and GE(2), the generalized entropy components of inequality.

**Figure 7.4 Distribution of Real Expenditure per Capita, Vietnam, 2006**




*Source:* Authors, based on Vietnam Household Living Standards Survey, 2006.

### Review Questions

| 5. In table 7.6, the single largest contributor to the reduction in poverty in Indonesia between 1984 and 1987 was: |
|---|
| ○ A. The reduction in poverty among farmers.<br>○ B. Workers leaving agricultural employment and moving to the cities.<br>○ C. Lower rates of urban poverty.<br>○ D. Slower population growth. |

| 6. According to figure 7.2, in Cambodia in 1999, |
|---|
| ○ A. The headcount poverty rate was highest for six-person households.<br>○ B. Eight-person households contributed the most to overall poverty.<br>○ C. Poverty among three-person households was significantly lower than among four-person households.<br>○ D. We are about 95% confident that the headcount poverty rate for two-person households is between 4% and 17%. |

| 7. The steps taken in poverty mapping include all of the following *except*: |
|---|
| ○ A. Build a model of the determinants of consumption, based on household survey data.<br>○ B. Use the household survey data to compute poverty rates for small areas within the country.<br>○ C. Use predicted consumption to estimate poverty rates in small areas.<br>○ D. Apply a model based on survey data to census data, and predict consumption for every household. |

| 8. The ADePT 2.0 program is designed to: |
|---|
| ○ A. Work as a stand-along program to generate standard tables and graphs quickly and easily.<br>○ B. Work within Stata to generate standard tables and graphs quickly and easily.<br>○ C. Work well to generate measures of poverty, provided that sample weights are not used.<br>○ D. Work well at generating specialized measures of inequality. |

## Note

1. This is a living standards measurement survey; see http://go.worldbank.org/MSCLPQKKY0 for further details.

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