CHAPTER VIII. ANALYSIS OF POVERTY DYNAMICS

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Introduction

Chapter 7 focused almost exclusively on analysis of poverty at a single point in time. Yet, in a given time period, people may be poor either because they've always been poor or because they have suffered a negative shock that temporarily pushed them below the poverty line. With a single cross-sectional survey, it is difficult to separate these two types of poverty even though each may require different policy prescriptions. Therefore, this chapter extends the analysis of Chapter 7 to many time periods, and thus it, it is concerned with the dynamics of poverty.

Examining changes in poverty over time raises difficult issues. But it also provides a richer and more realistic portrait of the nature of poverty. Individuals and households typically live for many decades, which implies that a person's poverty status may change over time. If it does not change over time, it would be trivial to extend static analysis to dynamic settings. As will be seen below, the poverty status of many individuals and households appears to change a great deal over time, a finding that is surprising to both researchers and policymakers.

This chapter assumes that "income" is an effective variable for measuring welfare. While this assumption may narrow the scope of poverty analysis, it is needed to keep the size of this chapter manageable. Even with a single–variable study, many important issues can arise in dynamic analysis that are not simple to resolve. Thus, despite the increased interest in poverty dynamics[53] collecting and analyzing survey data on poverty dynamics is a difficult task for any statistical agency. The chapter starts by examining three important conceptual issues in poverty analysis in Section 8.1:

- Relationship between income inequality and poverty at a single point in time and income mobility over time,
- Distinction between chronic and transient poverty, and
- Issues concerning the measurement of income growth among the poor.

Section 8.2 then examines two key practical issues: the relative merits of panel data and repeated cross-sectional data, and the problem of measurement error in income and expenditure data. Examples of how to analyze poverty dynamics are then presented in Section 8.3. Section 8.4 concludes the chapter by summarizing its findings and proposing several recommendations that would improve the analysis of poverty dynamics.

8.1 Conceptual issues

The possibility that people's poverty status can change over time raises several conceptual issues. This section discusses three of the most important:

[53] For examples, *see Journal of Development Studies*, August 2000 and *World Development*, March 2003,

- Understanding the relationship between income inequality and income mobility at a single point in time (which has direct implications for the relationship between income mobility and the dynamics of poverty),
- Distinguishing between chronic (long-run) and transient (short-run) poverty, and
- Measuring income growth of the poor.

8.1.1 Relationship between inequality and mobility

Assuming that income, or some other measurable variable, is a reasonably good indicator of welfare, poverty can be defined by a person's income relative to some poverty line. One's income determines one's poverty status, and changes in one's income effects changes in one's poverty status. Therefore, it is useful to begin by examining the distribution of income, and changes in the distribution of income before discussing poverty and changes in poverty.

First consider the relationship between income inequality at a single point in time and income mobility over time. For simplicity, consider a scenario with only two time periods. Let y_1 and y_2 be income in time periods 1 and 2, respectively. If people's incomes were unchanged in both time periods, then the distribution of y_1 would be the same as the distribution of y_2. The extent of poverty (measured by comparing the distribution of income to some poverty line) would be unchanged over time (and the poverty status of all individuals would be the same in both time periods). But the converse does not hold; the finding that the distribution of income has not changed over time, and thus that the extent of poverty is the same in both time periods, does *not* imply that everyone's income (and poverty status) is unchanged. It is also possible that some people who were poor in the first period escaped from poverty in the second period, while an equal number of people who were not poor in the first time period fell into poverty in the second period.

If it were the case that everyone's incomes had remained unchanged over time, then the correlation coefficient between y_1 and y_2 would equal one: $\rho(y_1, y_2) = 1$. On the other hand, if some people's incomes had increased between the two time periods so that they escaped poverty, and they were replaced by an equal number of people who fell into poverty over time, then the correlation between y_1 and y_2 would be less than one: $\rho(y_1, y_2) < 1$. Another way of expressing this phenomenon is to say that there is a certain amount of income mobility. Indeed, a common measure of income mobility, which can be denoted by $m(y_1, y_2)$, is one minus the correlation coefficient:

$$m(y_1, y_2) = 1 - \rho(y_1, y_2) \qquad (1)$$

where $\rho(\ln(y), \ln(x))$ is the correlation coefficient. For a more detailed exposition on mobility, see Glewwe (2005).

In general, for a given level of short-run inequality (inequality measured at one point in time), higher mobility implies a more equal distribution of long-run or "life cycle" income. For example, one commonly used measure of income inequality is the variance of the (natural) logarithm of income: Var[ln(y)]. In the simplest case, with only two time periods, long-run income can be calculated as the sum of income in the two time periods: $y_1 + y_2$. A common measure of income mobility across two time periods is based on the correlation of the log of income:

$$(y_1, y_2) = 1 - \rho(\ln(y_1), \ln(y_2))^{54} \qquad (1a)$$

If the degree of inequality in the two time periods is similar, then long-run income inequality is approximately equal to short-run inequality multiplied by one minus the mobility index:

$$\mathrm{Var}[\ln(y_1+y_2)] \approx \mathrm{Var}[\ln(y_1)](1 - m(y_1, y_2)) \qquad (2)$$

where $m(y_1, y_2)$ is defined as $1 - \rho(\ln(y_1), \ln(y_2))$. In other words, higher income mobility leads to lower long-run inequality for a given level of short-run inequality.

8.1.2 Chronic vs. transient poverty

If poverty is defined as having an income below some poverty line in any given year, greater mobility reduces the chance that a person who is poor in one time period is poor in another time period (for a given rate of poverty). In fact, if the logarithm of income (or any other monotonic transformation of income) is normally distributed in both years, the probability that a person is poor in both years decreases as the correlation

[54] In practice, it usually makes little difference whether mobility is defined as $1 - \rho(y_1, y_2)$ or $1 - \rho(\ln(y_1), \ln(y_2))$. Both of these mobility indices satisfy virtually all axioms that a reasonable measure of mobility should have (see, Glewwe, 2005).

coefficient of y_1 and y_2 decreases. Put another way, greater income or expenditure mobility implies that poverty is more of a temporary than a permanent phenomenon, and thus that poverty is more equally distributed across the population over an individual's lifetimes.

The degree of income mobility, and thus the difference between short-run and long-run inequality and the nature of poverty dynamics, is an empirical question. With adequate data, one can measure income mobility and its consequences for long-run inequality and the dynamics of poverty. Yet, this immediately leads to the question: How should one measure long-run poverty at both the individual and the aggregate level? In practice, two approaches are used to measure long-run poverty and to decompose poverty at one point in time into a long-run, chronic component, and a short-run transient component.

The first approach is the *Spells* approach, which focuses on the number of spells of poverty experienced over a given number of time periods. This approach classifies as chronically poor all those whose welfare is below the poverty line in all time periods. At any point in time, the poor can be divided into the chronically poor and the transient poor, the latter of which are poor at that time period but are not poor in one or more of the other time periods. For multiple time periods, one can calculate the population that is chronically poor ("always poor") and the average population that is transient poor. The chronically poor divided by the sum of the chronically poor and the average of the transient poor can be used to indicate the relative contribution of chronic poverty to overall poverty. The Spells approach tends to find that transient poverty is much more common than chronic poverty. In a review of 13 studies, 11 found that the chronically poor were a smaller proportion of the overall population than the transient poor (Baulch and Hoddinott, 2000).

There are several disadvantages of using the Spells approach to divide overall poverty into chronic and transient poverty. First, it is sensitive to measurement error, which leads to overestimation of the proportion of the population that is poor in some time periods but not in others. Second, it focuses attention on the headcount measure of poverty. In contrast, the poverty gap and distributionally-sensitive poverty measures (see Chapter 7) may record greater amounts of chronic poverty (as a proportion of overall poverty) because at a single point in time the chronic poor are most likely to be further below the poverty line. Third, the results are very likely to be sensitive to how many survey waves are available. It is harder for a household to be recorded as always poor in ten successive surveys than in just two of them. Similarly, when there are, say, ten survey waves, "sometimes poor" includes those who are poor once in ten periods and those who are poor in nine times out of ten, which is probably too broad a group to be meaningful. For example, across eight waves of data in the Russian Longitudinal Monitoring Survey (RLMS), gathered between 1994 and 2003, only four percent of urban households were always poor, while 81 percent were sometimes poor. But if only two waves of data are used (averaging over all possible combinations), 19 percent appear to be always poor and 36 percent appear to be sometimes poor. The ratio of always-to-sometimes poor, which can indicate chronic poverty, is thus not easily compared across surveys where households are observed across a different number of time periods.

An alternative method to the Spells approach is to divide poverty into the permanent component of a household's income (or consumption expenditures) and the remaining poverty due to transitory changes in income (Jalan and Ravallion, 1998). Under this C*omponents* approach, the chronically poor are those whose mean welfare across time is below the poverty line. The extent of chronic poverty is a function of that household's mean income, $C_i = P(\bar{y}_i, \bar{y}_i, \ldots, \bar{y}_i)$, where $\bar{y}_i$ is the mean welfare for household *i* over the T time periods spanned by the survey, and P is a poverty measure, such as the headcount or poverty gap. Transient poverty is the remainder, when C_i is subtracted from the total poverty measure at each point in time:

$$T_i = P(y_{i1}, y_{i2}, \ldots, y_{iK}) - P(\bar{y}_i, \bar{y}_i, \ldots, \bar{y}_i).$$

A simple example can help distinguish between the Spells and Components approaches. Consider four individuals, whose two-period consumption vectors are: A={450, 450}, B={400, 550}, C={530, 460}, and D={600, 550}. The poverty line is set at 500 in both periods. It is clear that person A is always poor, while B and C are sometimes poor, and D is never poor. Using the Spells approach to measure chronic poverty, one might conclude that the chronic poverty share of total poverty is one-third. However, persons A, B, and C are all chronically poor under the Components approach because their average consumption over time is below the poverty line.

The Components approach measures poverty in each period, using the period-specific consumption, and subtracts from this the poverty measure at the person's average consumption. For example, using the poverty gap index, the total poverty measures are:

- [((500-450)/500)+ ((500-450)/500)]/2=0.10, for person A
- [((500-400)/500)+ 0]/2=0.10, for person B, and
- [0+ ((500-460)/500)]/2=0.04, for person C.

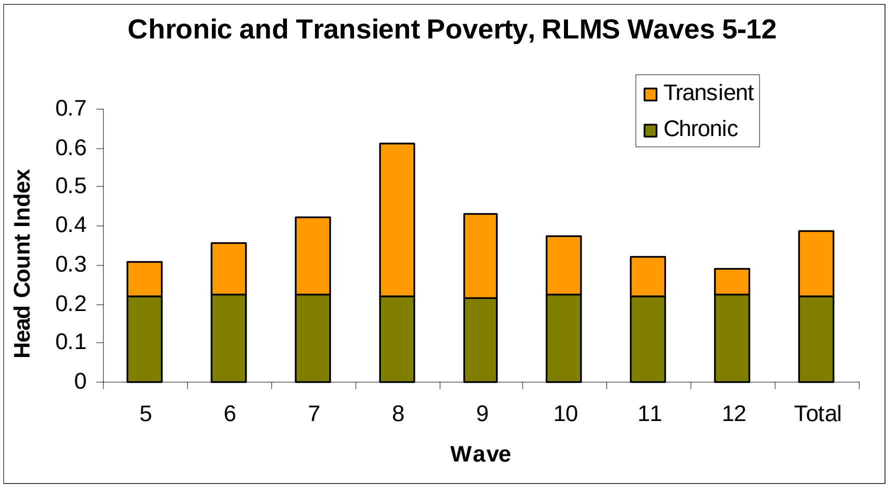
The chronic poverty measures are:

- (500-450)/500)=0.10, for person A
- (500-475)/500)=0.05, for person B, and
- (500-495)/500)=0.01, for person C.

Therefore, the transient components are 0, 0.05 and 0.03, respectively. Aggregating over the whole population of three people, the total poverty gap index is 0.06, the chronic poverty index is 0.04, and the transient poverty index is 0.02. In contrast to the Spells approach, two-thirds of the poverty appears to be chronic and only one-third transient.

This example highlights the impact various methodological approaches have on conclusions drawn about chronic and transient poverty. A further example comes from the RLMS data referred to above. According to the Components approach, chronic poverty makes up 57 percent of the total amount of poverty, and it is only during Wave 8 (in 1998 during the Russian financial crisis) that the contribution from transient poverty exceeds that from chronic poverty (Figure 1).

Figure 1: Chronic and Transient Poverty in Russia, 1994-2003



Source: Authors' calculations using the RLMS data.

8.1.3 Comparing Income Growth among Poor and Non-Poor Households

A major debate in economics is the extent to which a country's overall economic growth reaches all income groups, and especially if it raises the income of the poor as much as it does the incomes of more affluent groups. At first glance, the issue appears to be a relatively simple one. Yet, the rate of income growth among the poor depends on whose incomes are compared over time. Should one compare the incomes of the people who were poor in the first time period to the same people in the later time period (some of whom may no longer be poor), or should they be compared to the people who are poor in the later time period (some of whom were not poor in the first time period)? As long as some mobility exists, the first type of comparison will show a greater rate of economic growth among the poor than the second type of comparison. Which comparison is correct? Both are informative, and both need to be considered when asking whether economic growth has been "pro-poor."

8.2 Data issues

All the issues discussed in the previous section assume that once the conceptual issues are settled, data will be available to measure poverty and changes in poverty in accordance with the concepts deemed to be most correct. Yet, data from both developed and developing countries often fall short of the needs of researchers and policymakers who are interested in poverty issues. This section focuses on two important issues: the strengths and weaknesses of panel data and repeated cross-sectional data, and the problem of measurement error in the data.

8.2.1 Panel Data versus Repeated Cross-Sectional Data

Poverty dynamics is almost always measured by examining household survey data collected at two or more time periods. A very important characteristic of a household survey is whether the data are collected from the same households and individuals over time (called panel data) or if the data are collected from different households each time the survey is conducted (known as a repeated cross-sectional survey). In general, panel data provide much more information on poverty dynamics than do repeated cross-sectional data. But panel data are somewhat more complicated to collect.

To see the benefit of panel data, first consider the persistence of poverty over time, which, as explained above, is closely related to income mobility. Neither income mobility nor persistence of poverty can be measured using repeated cross-sectional data. Only panel data track the same people and households over time and thus reveal the extent to which people's incomes change over time, and the extent to which poverty is either permanent or temporary. Thus, panel data are required to separate overall poverty into its chronic and transient components. Second, consider the impact of economic growth on the poor. Both cross-sectional and panel data can be used to measure income growth among the poor if the poor are defined in terms of the current status (e.g., the poorest 20 percent of the population in each year). However, only panel data allow one to examine income growth among the poor when it is defined as following the same people over time (and thus who may not be in the poorest 20 percent of the population in later years). Again, the reason for this is that panel data track the same people and households over time, while cross-sectional data collect data from different people over time.

While panel data have the above-mentioned advantages, they also have three potential disadvantages. First, under even the best circumstances some households and individuals that are part of the original data are lost--they refuse to participate or cannot be found in later interviews. This phenomenon is known as sample attrition, and if the individuals and households that cannot be reinterviewed are systematically different from those that remain, the latter are not a random sample of the population and thus may yield biased estimates. Second, as new people are born and new households are formed, there is often a tendency to exclude them from the sample because those people and households did not exist when the sample was originally collected. While this potential source of bias, known as selection bias, can be overcome in principal by following households that "split off" from the original households in the survey, doing so is difficult and in practice is often not done. The third disadvantage of collecting data is that it may be somewhat more expensive to collect than implementing a series of repeated cross-sectional surveys.

While these limitations of panel data must be taken seriously, such data still provide much more information on poverty dynamics over time than does a series of cross-sectional surveys that interview different households at each point in time. Because the effect of these disadvantages can be mitigated (see Glewwe and Jacoby, 2000), this chapter recommends that panel data be collected if one wants to analyze poverty dynamics. This is not a simple task, but it is feasible in many developing countries. Further analysis and recommendations for how to collect panel data can be found in Glewwe and Jacoby (2000).

8.2.2 Measurement Error

A second key issue is measurement error in the income (or expenditure) data. Empirical studies of poverty dynamics, and more generally of income mobility, typically use income and/or expenditure data collected from household surveys. Anyone who has seen how such data are collected understands that these variables are likely to be measured with a large amount of error, and many empirical studies (e.g., Bound and Krueger, 1991 and Pischke, 1995) have verified this.

Measurement error in the income variable will cause virtually any measure of mobility to overestimate true mobility because all fluctuations in measured income due to measurement error are mistakenly treated as actual income fluctuations. A similar finding holds with respect to poverty dynamics: random measurement error in the income or expenditure variable will overestimate movements into and out of poverty. This can be demonstrated formally for income mobility using correlation-based mobility measures. The objective is to estimate $m(y_1^*, y_2^*) = 1 - \rho(f(y_1^*), f(y_2^*))$, where asterisks denote "true" income, measured without error. For simplicity, set $f(y^*) = y^*$. (This analysis generalizes to any function $f(y^*)$ for which measurement error in y^* causes measured $f(y^*)$ to equal $f(y^*)$ plus an additive error term). Consider income in two time periods for a set of individuals or households. The correlation coefficient is:

$$\rho(y_1^*, y_2^*) = \frac{\sigma_{y_1^*,y_2^*}}{\sqrt{\sigma^2_{y_1^*}\sigma^2_{y_2^*}}} = \frac{\sigma_{y_1^*,y_2^*}}{\sigma_{y_1^*}\sigma_{y_2^*}} \qquad (3)$$

where $\sigma_{y1^*,y2^*}$ denotes covariance and σ_{y1^*} and σ_{y2^*} denote standard deviations.

If the measurement errors in both time periods are uncorrelated with y_1^* and y_2^*, and with each other, calculations based on observed income will underestimate $\rho(y_1^*, y_2^*)$ in (3) and thus overestimate mobility, $m(y_1^*, y_2^*) = 1 - \rho(y_1^*, y_2^*)$. The same is true even if the measurement errors are correlated over time, as long as the correlation of y_1^*

and y_2^* is greater than the correlation of their respective measurement errors. Formally, denote observed incomes as $y_1 = y_1^* + u + e_1$ and $y_2 = y_2^* + u + e_2$, where e_1 and e_2 are random errors and u is a random component that persists over time and thus introduces correlation between the overall measurement errors. Assume that e_1, e_2 and u are uncorrelated with each other and with y_1^* and y_2^*. Consider the correlation of y_1 and y_2:

$$\rho(y_1, y_2) = \frac{\sigma_{y_1^*,y_2^*} + \sigma_u^2}{\sqrt{(\sigma_{y_1^*}^2 + \sigma_u^2 + \sigma_{e_1}^2)(\sigma_{y_2^*}^2 + \sigma_u^2 + \sigma_{e_2}^2)}} \approx \frac{\sigma_{y_1^*,y_2^*} + \sigma_u^2}{(\sigma_{y_1^*}^2 + \sigma_u^2 + \sigma_{e_1}^2)} \qquad (4)$$

where $\rho(y_1, y_2)$ is the correlation of *observed* income in the two time periods. If the error terms are not correlated over time, then $\sigma_u^2 = 0$ and the second term in (4) is clearly greater than $\rho(y_1^*, y_2^*)$, as can be seen by comparison with (3). Intuitively, e_1 and e_2 add "noise" to y_1^* and y_2^*, which reduces the observed correlation of the two income variables and thus increases observed mobility.

Overall, there are serious problems with using panel data to measure income and poverty dynamics because of measurement error in the income (or expenditure) data. In general, measurement error will exaggerate the extent of income mobility and thus will exaggerate movements into and out of poverty. The appropriate statistical procedure to evaluate measurement errors depends on the data available. When there are panel data for three or more points in time, it is possible to evaluate measurement error using simple correlations and a minimum of assumptions, following an approach developed by Heise (1969). But when data are available at only two points in time, evaluating measurement error for fluctuating variables like income and consumption requires more sophisticated instrumental variables regression modelling methods (Glewwe, 2005). The simple correlation method is described in this section, while results from the regression approach, which is needed with two period panels, are described in Section 3.0.

Many statistical agencies are familiar with the "reliability index," which shows the share of the standard deviation of an observed variable that is due to the true phenomenon. For example, the actual years of education for a household head is s*. But a survey measures school years as s, which may include an error, so the reliability index is defined as $\lambda = \sigma_{s*}/\sigma_s$. The reliability index can be estimated if two observations are made on the same variable, even when each observation is potentially unreliable. Let $s_1 = s^* + u_1$ be the first observation on the household head's education and $s_2 = s^* + u_2$ a repeated observation some months later, where u_1 and u_2 are measurement errors. If these errors are uncorrelated with each other and with true values, the empirical correlation between the two reports on the household head's education is:

$$\rho(s_1, s_2) = \frac{\mathrm{cov}\left(s^* + u_1, s^* + u_2\right)}{\sqrt{\mathrm{var}\left(s^* + u_1\right) \times \mathrm{var}\left(s^* + u_2\right)}} = \frac{\mathrm{var}\left(s^*\right)}{\sqrt{\mathrm{var}(s_1) \times \mathrm{var}(s_2)}} = \lambda^2 \qquad (5)$$

In other words, the correlation coefficient between two observations on the same variable gives the ratio of the variance in the true variable to the (geometric) average variance of the repeatedly observed variables, which equals the square of the reliability index. These correlations can often be obtained from re-visit or post-enumeration surveys.

The reliability index cannot be directly applied to longitudinal data on income or consumption, because unlike years of education in the above example, the true values of income and consumption fluctuate over time. Thus a correlation of less than one for the consumption of the same household in two periods does not necessarily indicate measurement error and instead may reflect an inability to smooth consumption over time. However, if there are at least three waves in a longitudinal survey, it is possible to separate real dynamics from measurement error with minimal assumptions (Heise, 1969). Intuition suggests that the estimated correlation between a mis-measured variable, like household consumption in one period, and a realization of that variable in a subsequent period will be less than it would be in the absence of measurement error (as explained above). And this attenuation is proportional to the reliability index of the variable.

As an example, consider the reliability index for household consumption in the Russian Longitudinal Monitoring Survey. Let Y_{1994}, Y_{1995}, and Y_{1996} be the observed consumption for the 2,195 urban households in the survey in each of 1994, 1995 and 1996. The true but unknown consumption is X_{1994}, X_{1995}, and X_{1996}, which differs from the observed values due to measurement errors that are independent of each other, of time, and of the underlying variable: $Y_t = X_t + u_t \quad \forall t$. If the reliability of measuring consumption does not vary over time, the correlation between observed consumption in two years is: $\rho(Y_t, Y_{t+1}) = \lambda_{Yt}\lambda_{Yt+1}\rho(X_t, X_{t+1}) = (\lambda_Y)^2\rho(X_t, X_{t+1})$. So for example, the correlation of 0.42 between observed expenditures in 1994 and 1995 understates the correlation in actual consumption by a factor of $(\lambda_Y)^2$. These assumptions also imply that

$\rho(Y_{t-1}, Y_{t+1}) = (\lambda_Y)^2\rho(X_{t-1}, X_{t+1})$. If realizations of the true values of consumption come from a first-order autoregressive model (that is, if $X_t = a + bX_{t-1} + e_t$), then the relationship between correlation coefficients is: $\rho(X_{t-1}, X_t)\times\rho(X_t, X_{t+1})/\rho(X_{t-1}, X_{t+1}) = 1$. Substituting in the results [Not clear] for the correlation in observed consumption, the reliability index is estimated as: $\lambda_Y = \sqrt{\frac{\rho(Y_{t-1}, Y_t)\rho(Y_t, Y_{t+1})}{\rho(Y_{t-1}, Y_{t+1})}}$. Applying this formula to the Russian data, $\lambda_y = \sqrt{\frac{\rho(Y_{1994}, Y_{1995})\rho(Y_{1995}, Y_{1996})}{\rho(Y_{1994}, Y_{1996})}} = \sqrt{\frac{0.42\times 0.51}{0.29}} = 0.86$.

In other words, the standard deviation of observed household consumption in the Russian data can be decomposed into a true component, which contributes 86 percent, and an error component, which contributes 14 percent. It is because of this error, which attenuates correlations, that the product of the two one-year apart correlations, $0.42\times 0.51\,(=0.22)$, is less than the two-year apart correlation, 0.29.

A further example of this reliability index calculation comes from the Indonesian Family Life Survey, which observed a panel of households in 1993, 1997 and 2000. The correlations between the logarithm of annualized expenditures in each of these three years are reported in Table 1. It is apparent that there was a closer relationship between expenditures in 1997 and in 2000 than between 1993 and 1997, which may reflect some changes in the questionnaire.[55] The measure of mobility for 1997-2000, $1 - \rho(\ln(y_1), \ln(y_2))$ gives values of 0.32-0.40 similar to those reported for Vietnam in Table 5 below. However, this measure of mobility is based on attenuated correlation coefficients, where

[55] Correlations between other variables, like age of the household head, which should be measured with less error, also show this pattern. Researchers should use such correlations to check that they have correctly identified panel households.

the attenuation is given by λ_Y^2. The estimates of λ_Y^2 vary from 0.68-0.73 by sector and once these are used to correct the correlations for the effect of measurement error, the mobility measures fall substantially to only 0.06-0.12.

Table 1: Correlations Between Annualized Expenditures and Mobility of Households in Indonesia, With Correction for Measurement Error

Correlations	Indonesia	Urban	Rural
1993_2000	0.4288	0.4362	0.3322
1993_1997	0.4684	0.4656	0.3785
1997_2000	0.6717	0.6775	0.6
Reliability ratio	0.73	0.72	0.68
Reliability index	0.86	0.85	0.83
Mobility index (1997-2000)	0.33	0.32	0.40
Corrected correlation (1997-2000)	0.92	0.94	0.88
Corrected mobility index	0.08	0.06	0.12

Source: Authors' calculations using Indonesian Family Life Survey (IFLS) data

8.3 Recommendations for Data Collection

Evidence of measurement error in the expenditure data from the Russian and Indonesian panels, which are two of the better regarded surveys from developing countries, illustrates the need to address this issue. Fortunately, panel data allow one to use methods that assess and correct for measurement error, methods that cannot be used with cross-sectional data. If statistical agencies in developing countries are interested in measuring poverty dynamics, they will need to collect panel data. This subsection provides some recommendations for doing so.

First, it is important that the sample involve households (or even more thoroughly, of individuals) rather than dwellings. Otherwise, replacing an old household with a new one in a sampled dwelling may create spurious evidence of changes in economic status. More specifically, any panel sample that returns to the same dwellings over time must collect sufficient data to ascertain whether the dwelling's inhabitants are the same household or a new household. (Methods for doing so are provided in Glewwe and Jacoby, 2000.) A better approach would be for the survey to follow households that move and those that split and re-form (e.g., following marriage and divorce) because the poverty status of movers is often different from that of people who maintain stable addresses and family circumstances.

Second, consideration must be given to sample attrition, which may lead to selective samples of stayers that yield misleading inferences about the population. Fortunately, for some purposes, sample attrition may not be a serious problem. For example, Falaris (2003) studied attrition in several LSMS surveys. Stayers were 31 percent of the initial sample for Peru between 1991 and 1994, 55 percent for Lima between 1985 and 1990, 82 percent for Côte d'Ivoire between 1985 and 1988, and 84 percent for Vietnam between 1993 and 1998. Despite this wide variation in attrition rates, regression relationships for schooling attainment, wages and other socio-economic outcomes do not seem to vary between "attritors" and stayers in these samples. Lack of attrition bias suggests that results from just the sample of stayers are also likely to apply to attritors. Similar conclusions have been reached for regression studies on longitudinal data in developed countries (Fitzgerald, Gottschalk and Moffitt, 1998).

Yet, it is not clear whether the relatively minor affects of attrition on the conditional mean in regression studies also holds for poverty studies, which focus on the lower tail of the distribution. There is surprisingly little evidence on the effects of attrition on observed poverty dynamics in developing countries. However, at least in developed countries, it seems that attrition creates a bias. Cappellari and Jenkins (2002) use the British Household Panel Survey and find that a sample that excludes attritors would disproportionately exclude the poor and cause an overestimation of poverty persistence.

One way to reduce the potential for attrition bias is for statistical agencies to change the way in which they implement longitudinal surveys. Many surveys in developing countries attempt to re-interview respondents only if they live in the same dwelling in which they were previously interviewed. Failure to track movers presumably reflects concerns about cost and feasibility. Nevertheless, the experience of the Indonesian Family Life Survey shows that many movers can be successfully tracked, even when they move to a new province. In that survey, households who moved locally have initial characteristics that are more like those who stay in the same dwelling, whereas those who move longer distances are more like attritors. So there is considerable information gained by making the effort to track the movers (Thomas, Frankenberg and Smith, 2001).

8.4 Analytical methods with examples

8.4.1 Repeated cross-sectional data (including poverty monitoring)

If one has two or more cross-sectional data sets, one can use them to measure the extent, characteristics, and distribution of poverty across population groups, and how all of these things change over time. In addition, one can measure the average income of the poorest 10 percent, 20 percent, or 30 percent (or any percentage that is of interest) and see how the income of these groups changes over time. These percentile-specific comparisons provide one way of considering how the effect of growth at different points in income distribution might affect poverty.

An alternative method, which also requires only repeated cross-sections, is to decompose the change in poverty between two surveys into a "distribution" component and a "growth" component. The distribution component reflects the hypothetical effect of changes in inequality while holding mean (real) income constant. In contrast, the growth effect allows (real) mean to change at the rate of economic growth while (counterfactually) holding the distribution of income (as measured by the Lorenz curve) constant. This decomposition is of interest because the appropriate policies for reducing poverty will depend on whether recent changes in poverty are due mainly to growth effects or to inequality effects.

This subsection presents examples of all of these, mainly using household survey data from Vietnam and Papua New Guinea. Vietnam is an interesting example because its high rate of economic growth led to a large decline in poverty, from about 58 percent in 1992-93 to about 37 percent in 1997-98 (World Bank, 1999). In such circumstances, it is usually clear that the growth component of the poverty change is dominant. In contrast, poverty in Papua New Guinea has been much more persistent (Gibson, 2000). Therefore, to provide an example where it is less clear whether it is the growth or the inequality component that is likely to dominate, this subsection illustrates decomposition methods using data from urban Papua New Guinea.

Table 2 shows the extent of poverty in Vietnam in 1992-93 and 1997-98 using two common poverty indices: the headcount index (proportion of the people who are poor) and the poverty gap index (see Chapter 7 for an explanation).[56] Figures are shown separately for urban and rural areas, as well as for the entire country. The incidence of poverty in Vietnam dropped from 58.1 percent in 1992-93 to 37.4 percent in 1997-98. The drop in the poverty gap is even more dramatic, cut almost in half from 0.185 to 0.095. Using either index of poverty, it is clear that poverty dropped much more rapidly in urban areas than in rural areas. For example, in urban areas the incidence of poverty declined by more than half, from 25.1 percent to 9.0 percent, while in rural areas the poverty rate dropped from 66.4 percent to 44.9 percent.

Table 2: Poverty in Vietnam in 1992-93 and 1997-98

[56] For more information on the 1992-93 and 1997-98 Vietnam Living Standards Survey, see World Bank (2001).

	Urban		Rural		All Vietnam	
	Headcount	*Pov. Gap*	*Headcount*	*Pov. Gap*	*Headcount*	*Pov. Gap*
1992-93	0.251	0.064	0.664	0.215	0.581	0.185
1997-98	0.090	0.017	0.449	0.116	0.374	0.095

Source: Authors' calculations using Vietnam Living Standards Survey (VLSS) data.

Table 3 shows how the distribution of poverty has changed over time. In 1992-93, the share of poverty in the Northern Uplands was only slightly higher than its share of the total population (21 percent versus 18 percent, respectively). However, by 1997-98, its share of poverty had increased to almost 28 percent. In contrast, the share of poverty in the Red River Delta in 1992-93 was higher than its population share (23 percent versus 20 percent, respectively). But by 1997-98, the share of poverty in that region had dropped to 15 percent. This region contains the capital city of Hanoi, which experienced very high economic growth during the 1990s. The positive impact of urban economic growth on poverty is also apparent in the Southeast region, which includes Ho Chi Minh City . The share of poverty in that area was already lower than its population share in 1992-93 (7 percent versus 13 percent, respectively). And by 1997-98, its share of poverty had declined even further to only 3 percent.

Table 3: Distribution of Poverty in Vietnam, by Region

	Share of Poverty (Headcount Index)		**Share of Population**
Region	**1992-93**	**1997-98**	
Northern Uplands	21%	28%	18%
Red River Delta	23	15	20

North Central	16	18	14
Central Coast	10	10	11
Central Highlands	4	5	4
Southeast	7	3	13
Mekong Delta	18	21	21
All Vietnam	100%	100%	100%

Source: Authors' calculations using VLSS data.

Another use of repeated cross-sectional data is to examine the income growth among the poorest 20 percent (or any percent) of the population, focusing on who is currently poor, not who was poor during the initial time period. This is shown in Table 4. The annual growth rate of per capita expenditures of the poorest 20 percent of the population from 1992-93 to 1997-98 was 6.5 percent, slightly below the national average rate of 7.1 percent. The annual growth rate of the wealthiest 20 percent was somewhat higher, at 7.7 percent, while the rates for the rest of the population was remarkably consistent, averaging between 6.7 and 6.9 percent.

Table 4. Growth Rates in Observed Expenditures

	Population Distribution in 1992-93 (percent)	Mean Per Capita Expenditures 1992-93	Mean Per Capita Expenditures 1997-98	Growth over 5 Years (percent)	Average Annual Growth Rate (percent)
All Vietnam	100	1876	2648	41.2	7.1
By current quintile					
Poorest 20%	20	800	1095	36.9	6.5
Next 20%	20	1169	1617	38.3	6.7
Middle 20%	20	1516	2093	38.1	6.7
Next 20%	20	2030	2840	39.9	6.9
Richest 20%	20	3867	5601	44.8	7.7

Source: Authors' calculations using VLSS data.

Decomposition of a change in poverty rates into growth and distribution components relies on the fact that the FGT poverty measures (see Chapter 3) can be fully characterized in terms of the poverty line, the mean income of the distribution, and the Lorenz curve, which represents the distribution of income (Datt and Ravallion, 1992):

$$P_t = P\left(z/\mu_t, L_t\right) \tag{6}$$

where z is the poverty line, μ_t is the mean income, and L_t is a vector of parameters fully describing the Lorenz curve. The growth component of a change in poverty between date t and date t + n is computed as the change in poverty due to a change in the mean while holding the Lorenz curve constant at some reference level L_r:

$$G\left(t, t+n; r\right) = P\left(z/\mu_{t+n}, L_r\right) - P\left(z/\mu_t, L_r\right) \tag{7}$$

Often, the reference period r will be the starting date for the decomposition so that r = t. The distribution component is computed as the change in poverty between dates t and t + n due to a change in the Lorenz curve while keeping the mean income constant at the reference level μ_r:

$$D\left(t, t+n; r\right) = P\left(z/\mu_r, L_{t+n}\right) - P\left(z/\mu_r, L_t\right) \tag{8}$$

A convenient way of holding the Lorenz curve constant so as to obtain the growth component (equation (7)) is to use a statistical program such as POVCAL,[57] which allows experiments with different mean expenditure levels and poverty lines. For example, Table 5 shows a decomposition of poverty in Papua New Guinea used data from surveys in 1986 and 1996. In the first step of the decomposition, the Lorenz curve was estimated from data collected from the first year (1986) of the study. If the parameters of this estimated curve are combined with the 1996 mean expenditure level (K2451) and poverty line (K956), counterfactual estimates of poverty rates in 1996 are derived. These counterfactual estimates show what would have happened to poverty rates if the observed real growth in consumption had occurred, but there had been no change in inequality (the Lorenz curve is held constant). Comparison of this counterfactual with the estimated poverty rate in the first survey gives the growth component of the poverty change.

To derive the inequality component, a Lorenz curve was estimated on the data for the second year (1996) and then combined with the 1986 mean expenditure level (K1093) and poverty line (K484). This gives a counterfactual of what the poverty rate would have been in the second year if there had been a change in inequality with no change in real mean consumption. A comparison of this counterfactual with the estimated poverty rate in the first survey gives the distribution component of the poverty change.

Table 5. Example of the decomposition of change in poverty in Papua New Guinea, from 1986 to 1996

[57] This program can be downloaded from http://www.worldbank.org/lsms/tools/povcal/. A more general tool for this purpose is SimSip, which is also freely available from the World Bank, and can do cross-sectional, temporal decompositions, and incidence analysis.

Measures	1986	1996	Change	Growth	Distribution	Residual
P_0	19.64	18.93	-0.71	-6.12	3.00	2.41
P_1	3.73	7.64	3.91	-1.74	5.47	0.18
P_2	0.94	4.28	3.34	-0.55	4.27	-0.38
μ	1093.1	2450.7	..	..	..	..
Gini	0.379	0.403	..	..	..	..
Z	484	956	..	..	..	..

Source: Authors' calculations using household survey data from Papua New Guinea.

The growth and distribution components will often not add up exactly to the amount by which the actual poverty rate changes between two surveys. This residual is apparent for the headcount poverty rate (P_1) in the example, which was largely unchanged between the two surveys, but is not very important for the other two poverty measures which did exhibit much larger increases.

In terms of the policy uses of this decomposition, it appears that the major source of the rise in the poverty gap (P_1) and squared poverty gap (P_2) between 1986 and 1996 in Papua New Guinea was the increased inequality in the income distribution. Knowing this may be helpful for the design of appropriate poverty reduction policies.

8.4.2 Panel data for two points in time

This subsection relies on data from Vietnam to demonstrate how household survey data can be used to study poverty dynamics when one has panel data for two time periods. As in the previous subsection, the data used are from the 1992-93 and the 1997-98 Vietnam Living Standards Surveys. This data set is of particular interest because 4,300 of the 4,800 households in the 1992-93 survey were re-interviewed in 1997-98 survey, providing a large, national representative panel data set. (In the previous subsection these data sets were treated as repeated cross-sections.)

For simplicity, this examination of mobility and the dynamics of poverty will use household expenditures per capita as the indicator of poverty. The poverty line used is defined as the amount of money needed to purchase a basket of goods (both food and nonfood) that follows typical Vietnamese expenditure patterns and provides 2,100 calories per person per day. (For further details, see, World Bank, 1999.) The panel data reveal a poverty rate of 56.2 percent in 1992-93 and 33.5 percent in 1997-98.

Section 8.1 emphasized the key role that income (or expenditure) mobility plays in determining poverty dynamics. Thus, the first step is to examine expenditure mobility across the two years in Vietnam. Table 6 provides information on *observed* expenditure mobility, which (as explained in Section 8.1) is likely to exaggerate the true level of expenditure mobility. The top part of Table 6 shows a "transition matrix" that indicates, for each of the two years, households' position across five quintiles, ranging from the poorest 20 percent of the population (quintile 1) through the wealthiest 20 percent (quintile 5).

This transition matrix reveals a large amount of apparent mobility. For example, almost half of the households that were in the poorest 20 percent of the population in 1992-93 were no longer in the poorest 20 percent in 1997-98. About 40 percent of the population that was in the highest quintile in 1992-93 was no longer in that quintile in 1997-98. More generally, only 40 percent of the population remained in the same quintile during both survey years. Another 40% percent moved up or down one quintile, while the other 20 percent moved up or down two quintiles. Overall, it appears that there is a substantial amount of mobility. Of course, measurement errors exaggerate this mobility. Figures that are based on attempts to remove measurement error are presented below.

Table 6: Per capita Expenditure Mobility in Vietnam from 1992-93 to 1997-98 (observed values)

A. Mobility Matrix, by Quintiles

		1997-98 Quintile					
		1	2	3	4	5	Row Total
1992-93 Quintile	1	445	229	124	51	8	857
		(10.4%)	(5.5%)	(2.9%)	(1.2%)	(0.2%)	(20.0%)
	2	239	255	215	113	34	856
		(5.6%)	(6.0%)	(5.0%)	(2.6%)	(0.8%)	(20.0%)
	3	111	208	217	229	91	856
		(2.6%)	(4.9%)	(5.1%)	(5.4%)	(2.1%)	(20.0%)
	4	46	126	211	280	193	856
		(1.1%)	(2.9%)	(4.9%)	(6.5%)	(4.5%)	(20.0%)
	5	16	38	90	182	530	856
		(0.4%)	(0.9%)	(2.1%)	(4.3%)	(12.4%)	(20.0%)
Column Total		857	856	857	855	856	4281
		(20.0%)	(20.0%)	(20.0%)	(20.0%)	(20.0%)	(100.0%)

Remained in same quintile in both years: 40.3%

Moved up or down by one quintile: 39.9%
Moved up or down by two or more quintiles: 19.8%

B. Summary Measures of Mobility

$m(x, y) = 1 - \rho(x,y)$:	0.309
$m(x, y) = 1 - \rho(\ln(x), \ln(y))$	0.298
$m(x, y) = 1 - \rho(\text{rank}(x), \text{rank}(y))$	0.332

SOURCE: Authors' calculations using VLSS data.

The bottom half of Table 6 presents summary measures of expenditure mobility based on correlation between per capita expenditures in 1992-93 and 1997-98. Three different versions are presented, based on correlations of expenditures, the natural log of expenditures, and the rank of expenditures. The results are quite similar, showing mobility ranging from 0.298 to 0.332. Note that no mobility at all would give a value of zero and "full" mobility, in the sense of no correlation of expenditure over time, would give a mobility index of 1. While these figures are closer to "no mobility" than to "full mobility," the transition matrix indicates that, intuitively, this is still a substantial amount of mobility.

Using the poverty lines developed by the World Bank, the dynamics of poverty are shown in Table 7-A. Of the households that were poor in 1992-93, almost half (27.4 percent, relative to 56.2 percent) were no longer poor in 1997-98. Of the households that were not poor in 1992-93, slightly more than one tenth appear to have become poor in

1997-98 (4.7 percent out of 43.8 percent). This implies that 28.8 percent of the population was poor in both time periods.

Table 7-B also presents figures on decomposition of poverty into its chronic and transient components using the two methods described above. The spells method, which is based on the head count index, indicates that about half of overall poverty is chronic (poor in both time periods), while half is transient (poor in only one of the two time periods). This same pattern is found in rural areas where 80 percent of Vietnamese live. But in urban areas, only about one fourth of overall poverty is chronic, which reflects that most people in urban areas in the first time period were no longer poor in the second time period. The last set of figures in Table 7-C decomposes poverty into its chronic and transient components using the components method, which can be used not only for the headcount index but also for indices that are sensitive to the depth of poverty. For Vietnam as whole, they show that most of the poverty is chronic, which means that most

Table 7: Poverty Dynamics in Vietnam from 1992-93 to 1997-98
(based on observed values of per capita expenditures)

A. Poverty Transition Matrix

		Poverty Status in 1997-98		
		Poor	Non-poor	Row Total
Poverty Status in 1992-93	Poor	1233 (28.8%)	1172 (27.4%)	2405 (56.2%)
	Non-poor	200 (4.7%)	1676 (39.2%)	1856 (43.8%)
	Column Total	1433 (33.5%)	2848 (66.5%)	4281 (100.0%)

B. Decomposition into Chronic and Transient Poverty (Spells Method)

Proportion of the Population that is:	*All Vietnam*	*Urban*	*Rural*
Never Poor	39.2%	74.0%	31.1%
Poor in 1 period (transient poverty)	32.1%	19.5%	34.9%
Poor in both periods (chronic poverty)	28.8%	6.5%	34.0%
Proportion of Poverty that is Chronic	47.3%	25.0%	49.3%

C. Decomposition into Chronic and Transient Poverty (Components Method)

	Headcount	*Poverty Gap*	*Squared Poverty Gap*
Overall Poverty	0.448	0.128	0.051
Transient poverty	0.031	0.024	0.015
Chronic poverty	0.417	0.104	0.037
Proportion of Poverty that is Chronic	93.1%	81.0%	71.7%

Source: Authors' calculations using VLSS data.

of the poverty is due to individuals whose average expenditures over the two years fall below the poverty line. This proportion declines (although it is still large) as the poverty measure becomes more sensitive to the depth of poverty. This is intuitively plausible because the more sensitive an index is to the depth of poverty, the more weight the transient component gives to a household that is very poor in one year but not poor in the other year (relative to the chronic component, which considers just the average income over the two years).

As explained above, it is almost certain that household expenditures are measured with a large amount of error and thus exaggerate mobility and thus movements in and out of poverty. Glewwe (2005) presents evidence that at least 15 percent of estimated mobility is measurement error. Tables 8 and 9 use simulation methods to estimate mobility under two different assumptions. The portion of measured mobility attributable to measurement error in one case is 15 percent ("lower estimate") and 25 percent ("higher estimate") in the other. These simulations are based on the assumption that the logarithm of per capita expenditures is normally distributed. (See Glewwe and Dang (2005) for evidence of the reasonableness of this assumption.)

The top part of Table 8 reproduces the transition matrix under the two assumptions about the contribution of measurement error to observed mobility of per capita expenditures. Turning to the higher estimate of the contribution of measurement error, there is still a lot of movement across the expenditure quintiles over time, but not as much as in Table 6. Recall that in Table 6 about one half of the households that were poor in 1992-93 were no longer poor in 1997-98. When the higher estimate of measurement error is assumed, about 38 percent of the poor in 1992-93 are no longer poor in 1997-98. More generally, while the observed data shown in Table 6 suggests that only 40 percent of the population remains in the same quintile in both years (and 20 percent move up or down by two or more quintiles), this number increases to about 45 percent

Table 8: Per capita Expenditure Mobility in Vietnam from 1992-93 to 1997-98 (simulated values that correct for measurement error)

A. Mobility Matrix, by Quintiles (percent distribution of 50,000 simulated observations)

Lower bound estimate of measurement error

		1997-98 Quintile					
		1	2	3	4	5	Row Total
	1	12.0	5.1	2.2	0.6	0.1	20.0
1992-93	2	5.1	6.5	5.1	2.7	0.7	20.0
Quintile	3	2.2	5.0	5.8	4.8	2.3	20.0
	4	0.7	2.7	5.0	6.6	5.0	20.0
	5	0.1	0.7	2.0	5.3	11.9	20.0
	Column Total	20.0	20.0	20.0	20.0	20.0	100.0

Remained in same quintile in both years:	42.8%
Moved up or down by one quintile:	40.3%
Moved up or down by two or more quintiles:	16.9%

Higher estimate of measurement error

		1997-98 Quintile					
		1	2	3	4	5	Row Total
	1	12.5	5.0	2.0	0.5	0.1	20.0
1992-93	2	5.0	6.9	5.2	2.5	0.5	20.0
Quintile	3	2.0	5.0	6.1	4.9	2.0	20.0
	4	0.5	2.6	5.0	6.9	5.0	20.0
	5	0.1	0.5	1.8	5.2	12.4	20.0
	Column Total	20.0	20.0	20.0	20.0	20.0	100.0

Remained in same quintile in both years:	44.8%
Moved up or down by one quintile:	40.2%
Moved up or down by two or more quintiles:	15.0%

B. Summary Measures of Mobility

Estimate of Measurement Error Estimate	*Lower bound*	*Higher*
m(x, y) = 1 – ρ(x,y):	0.284	0.250
m(x, y) = 1 – ρ(ln(x), ln(y))	0.254	0.225
m(x, y) = 1 – ρ(rank(x), rank(y))	0.271	0.240

SOURCE: Authors' calculations using VLSS data.

(decreases to 15 percent) when measurement error is assumed to account for 25% of mobility. Of course, when actual measurement error is assumed to by smaller (the "lower bound estimate"), the differences with Table 6 are smaller. Thus, the observed data do overestimate income mobility but adjusting for measurement error still leaves a substantial amount of mobility in Vietnam.

Turning to the bottom of Table 8, the summary measures of mobility show that the percent of mobility that is due to measurement error under the "lower bound assumption" ranges from 8 to 18 percent, depending on the mobility index used. This range increases to between 19 and 28 percent when the "higher assumption" is used. (By definition, these figures are nearly 15 and 25 percent for the log variance measure, since the simulations are based on the assumption that the log of per capita expenditures is normally distributed.)

Table 9 presents simulation results for poverty dynamics similar to those presented in Table 7. However, Table 9 presents simulations that exclude measurement error. Turning to the poverty transition matrix, the proportion of households that are poor in both time periods is almost identical to the proportions shown in Table 5. However, the proportion of people who are poor in both time periods increases slightly from 28.8 to 30.4 percent (using the lower bound assumption on measurement error) or 30.6 percent (using the higher assumption on measurement error). Thus, accounting for measurement error does not change the general finding that there is substantial movement in and out of poverty over time. Table 9 also presents figures that decompose poverty into its chronic and transient components, using the two methods described above on the simulated data. The spells method, which is based on the head count index, indicates that slightly more than one half of overall poverty is chronic (poor in both time periods) while slightly less than half is transient (poor in only one of the two time periods).

Table 9: Poverty Dynamics in Vietnam from 1992-93 to 1997-98 (based on simulated values of per capita expend. that correct for measurement error)

A. Poverty Transition Matrix

Lower estimate of measurement error

		Poverty Status in 1997-98		
		Poor	Non-poor	Row Total
Poverty Status in 1992-93	Poor	30.4	25.7	56.1
	Non-poor	3.5	40.4	43.9
	Column Total	33.9	66.1	100.0

Higher estimate of measurement error

		Poverty Status in 1997-98		
		Poor	Non-poor	Row Total
Poverty Status in 1992-93	Poor	30.6	25.6	56.1
	Non-poor	2.9	40.9	43.9
	Column Total	33.5	66.5	100.0

B. Decomposition into Chronic and Transient Poverty (Spells Method)

	All Vietnam	
Proportion of the Population that is:	*Lower Bound of Measurement Error*	*Upper Bound of Measurement Error*
Never Poor	40.3	40.8%
Poor in 1 period (transient poverty)	29.2	28.7%
Poor in both periods (chronic poverty)	30.6	30.6%
Proportion of Poverty that is Chronic	51.2%	51.6%

C. Decomposition into Chronic and Transient Poverty (Components Method)

	Lower Bound of Measurement Error			*Upper Bound of Measurement Error*		
	Headcount	*Poverty Gap*	*Squared Poverty Gap*	*Headcount*	*Poverty Gap*	*Squared Poverty Gap*
Overall Poverty	0.451	0.144	0.064	0.449	0.141	0.061
Transient poverty	0.027	0.021	0.014	0.026	0.021	0.013
Chronic poverty	0.425	0.123	0.050	0.423	0.120	0.048
Proportion of Pov. that is Chronic	94.1%	85.3%	78.5%	94.2%	85.2%	78.6%

SOURCE: Authors' calculations using VLSS data.

This decomposition attributes about four percentage points more to chronic poverty than does the figure for Vietnam as a whole (47.3 percent) cited in Table 7. Thus measurement error in Table 7 underestimates the extent to which poverty is chronic, although the extent of underestimation is not very large. Note also that the higher the measurement error, the greater the extent of underestimation (the difference compared to the 47.3% figure in Table 7 is 3.9% for the lower bound and 4.3% for the upper bound), although this difference is very small. The last set of figures in Table 9 decomposes poverty into its chronic and transient components using the components method, again using the simulated data. For the headcount measure there is not much difference with the poverty rate figures in Table 7. Since poverty is close to 50 percent, measurement error is equally likely to misclassify a non-poor person as poor as it is to classify a poor person as non-poor. However, the proportion of poverty that is chronic increases slightly, which is consistent with the fact that measurement error tends to underestimate chronic poverty. This underestimation of the contribution of chronic poverty to overall poverty is even more pronounced for the measures that are sensitive to the depth of poverty.

The last issue this chapter examines using the panel data from Vietnam is if the country's economic growth has been "pro-poor." This can be seen be examining growth rates over time for each expenditure quintile. Table 10 shows this information using the data from the 4,300 panel households. For Vietnam as a whole, per capita expenditures rose by 41.2 percent over five years, which implies an annual rate of increase of about 7.1 percent. The remaining rows of Table 10 examine growth rates for each quintile. One way of examining economic growth among the different expenditure quintiles is to compare the expenditure levels of a given quintile in 1992-93 with the expenditure level of the corresponding quintile in 1997-98, which does not necessarily compare the same households. This can be done using both cross-sectional and panel

Table 10. Growth Rates in Observed Expenditures, Using Actual Data

	Population Distribution in 1992-93 (percent)	Mean Per Capita Expenditures 1992-93	Distribution of Per Capita Expenditures 1992-93 (percent)	Mean Per Capita Expenditures 1997-98	Distribution of Per Capita Expenditures 1997-98 (percent)	Growth over 5 Years (percent)	Average Annual Growth Rate (percent)
All Vietnam	100	1876		2648		41.2	7.1
By current quintile							
Poorest 20%	20	800	8.5	1095	8.3	36.9	6.5
Next 20%	20	1169	12.5	1617	12.2	38.3	6.7
Middle 20%	20	1516	16.2	2093	15.8	38.1	6.7
Next 20%	20	2030	21.6	2840	37.1	39.9	6.9
Richest 20%	20	3867	41.2	5601	42.3	44.8	7.7
By 1992-93 quintile							
Poorest 20%	20	800	8.5	1470	11.1	83.8	12.9
Next 20%	20	1169	12.5	1855	14.0	58.7	9.7
Middle 20%	20	1516	16.2	2328	27.4	53.6	9.0
Next 20%	20	2030	21.6	2848	21.5	40.3	7.0
Richest 20%	20	3867	41.2	4735	35.8	22.4	4.1

SOURCE: Authors' calculations using VLSS data.

data. (These results were shown in Table 4 and are given again in the top half of Table 10.) Recall that these results suggest that economic growth has been fairly equitable, with four of the five quintiles having annual growth rates of 6.5 to 6.9 percent. Only the wealthiest quintile has a somewhat higher growth rate--7.7 percent.

Growth rates are much more strongly pro-poor if the same households are compared over time, which is shown in the bottom half of Table 10. The poorest 20 percent of households in Vietnam surveyed between 1992-93 experienced an annual growth rate of 12.9 percent, which is almost double the national average of 7.1 percent and nearly three times as high as the growth rate experienced by the wealthiest quintile

(4.1%). Yet, the results in Table 10 may exaggerate the extent to which economic growth in Vietnam has been “pro-poor” in the second sense of examining the same households over time. As explained above, some of the movement of households across quintiles over time may reflect measurement error.

Tables 11 and 12 examine this by showing simulated growth rates after removing measurement error. Table 11 assumes a relatively low level of measurement error--about 15 percent of measured mobility--while Table 12 assumes that 25 percent of observed mobility is due to measurement error. The overall conclusion is that the patterns found in Table 10 do not change very much. More precisely, economic growth in Vietnam has been relatively pro-poor, especially when one compares the same households over time.

Table 11: Growth Rates in "True" (Unobserved) Expenditures, Using Simulated Data
(assuming that 15% of observed mobility is measurement error)

	Population Distribution in 1992-93 (percent)	Mean Per Capita Expenditures 1992-93	Distribution of Per Capita Expenditures 1992-93 (percent)	Mean Per Capita Expenditures 1997-98	Distribution of Per Capita Expenditures 1997-98 (percent)	Growth over 5 Years (percent)	Average Annual Growth Rate (percent)
All Vietnam	100	1956		2770		41.6	7.2
By current quintile							
Poorest 20%	20	758	7.8	1102	8.0	45.4	7.8
Next 20%	20	1226	12.5	1745	12.6	42.3	7.3
Middle 20%	20	1667	17.0	2353	17.0	41.2	7.1
Next 20%	20	2257	23.1	3183	38.0	41.0	7.1
Richest 20%	20	3871	39.6	5470	39.5	41.3	7.2
By 1992-93 quintile							
Poorest 20%	20	758	7.8	1508	10.9	98.9	14.7
Next 20%	20	1226	12.5	2056	14.8	67.7	10.9
Middle 20%	20	1667	17.0	2558	27.5	53.4	8.9
Next 20%	20	2257	23.1	3180	23.0	40.9	7.1
Richest 20%	20	3871	39.6	4551	32.9	17.6	3.3

SOURCE: Authors’ calculations using VLSS data

Table 12: Growth Rates in "True" (Unobserved) Expenditures, Using Simulated Data (assuming that 25% of observed mobility is measurement error)

	Population Distribution in 1992-93 (percent)	Mean Per Capita Expenditures 1992-93	Distribution of Per Capita Expenditures 1992-93 (percent)	Mean Per Capita Expenditures 1997-98	Distribution of Per Capita Expenditures 1997-98 (percent)	Growth over 5 Years (percent)	Average Annual Growth Rate (percent)
All Vietnam	100	1956		2770		41.6	7.2
By current quintile							
Poorest 20%	20	763	7.8	1089	7.9	42.7	7.4
Next 20%	20	1224	12.5	1741	12.6	42.2	7.3
Middle 20%	20	1660	17.0	2368	17.1	42.7	7.4
Next 20%	20	2256	23.1	3214	38.2	42.5	7.3
Richest 20%	20	3858	39.5	5455	39.3	41.4	7.2
By 1992-93 quintile							
Poorest 20%	20	763	7.8	1488	10.7	95.0	14.3
Next 20%	20	1224	12.5	2071	14.9	69.2	11.1
Middle 20%	20	1660	17.0	2557	27.5	54.0	9.0
Next 20%	20	2256	23.1	3183	23.0	41.1	7.1
Richest 20%	20	3858	39.5	4567	32.9	18.4	3.4

SOURCE: Authors' calculations using VLSS data

8.5 Conclusion

This chapter has described methods for analyzing changes in poverty over time. Some methods can be used with repeated cross-sectional data, while a richer set of methods can be used if panel data are available. Comparisons over time are prone to bias due to measurement error, so the chapter has also described some methods for observing and dealing with measurement error in income and expenditure data.

There are many factors that statisticians, economists and other researchers must consider when measuring poverty at a single point in time, and additional complications arise when examining how poverty changes over time. This paper has reviewed three important conceptual issues:

- Relationship between poverty dynamics and income mobility,
- Chronic poverty vs. transient poverty, and
- How to measure the impact of economic growth on the poor.

Two important data issues were also addressed:

- Relative merits of cross-sectional and panel data, and
- Problems due to measurement error.

This chapter provides lessons for statistical agencies in developed and developing countries on how to collect data that are useful for understanding the dynamics of poverty. Because poverty and poverty dynamics may vary significantly from country to country, and because most poor nations have only limited data – in particular, most lack panel data – it is not possible to draw general policy conclusions or even general conclusions about the nature of poverty dynamics. However, if this chapter's survey recommendations are followed, then each country will have the data necessary to understand poverty dynamics and to formulate poverty-reducing policies.

Perhaps the most important data collection recommendation is that all countries should attempt to collect nationally representative panel data. It may not be necessary to visit households every year; every two or three years may yield sufficiently useful data. (For detailed recommendations on collecting panel data, see Glewwe and Jacoby, 2000.)

The second key lesson is that measurement error is a serious problem that can lead to biased results. National statistical agencies should undertake comprehensive efforts to improve the accuracy of their household survey data, such as increasing supervision of field work and conducting validation studies. A third lesson is that there are methods that can be used to minimize bias due to measurement error when analyzing poverty data.

Study of poverty dynamics in both developed and developing countries is a relatively new area of research. Much more thinking is needed to refine underlying theoretical concepts, and to improve data collection and analysis. Statisticians, economists, and other researchers need to work together with statistical agencies to learn more about poverty dynamics in both developed and developing countries. This will lead to more effective poverty policies and, ultimately, to less poverty.

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