SOAS, Economics Working Paper Series, No. 129

Measurement and Nature of Absolute Poverty in Least Developed Countries

By

Massoud Karshenas
Department of Economics
SOAS, University of London
London
WC1H 0XG

E-mail mk@soas.ac.uk

Abstract:

This paper provides new national accounts consistent poverty estimates for low-income countries. The properties of the new estimates are compared to the existing estimates by the World Bank based on household survey means. We also use the new estimates to reflect on the recent controversies regarding the relationship between economic growth and poverty reduction. It is argued that the controversy is mainly due to the lack of distinction between what one can refer to as 'generalized extreme poverty' in low-income countries and the more 'normal' poverty situations in higher income economies.

November 2001

I am grateful to Graham Pyatt, Hashem Pesaran, Farhad Mehran, Charles Gore, Ben Fine, Mehdi Shafaeddin and Kurkut Boratov for comments on an earlier draft of this paper. I am also grateful to Marquise David for her able research assistance and to Utumporn Reiungsuwan for her invaluable support and encouragement. The paper was prepared as a background paper for the Least Developed Countries Report 2002, UNCTAD.

1. Introduction

Poverty reduction has become a central global policy objective. Some have even put forward proposals for allocation of international aid according to poverty reduction performance. Little attention, however, has been paid to the fact that we do not as yet have reliable and consistent measures of poverty suitable for inter-country comparisons for low-income countries. International comparison of poverty poses vexing conceptual and measurement problems, which have been extensively discussed in the literature. Three basic sets of conceptual and methodological issues are involved in measuring absolute poverty in low-income countries: (i)- the choice of an appropriate poverty index, (ii)- the choice of an absolute poverty line, and (iii)- the choice of a metric and the measurement of its distribution. In this paper we are mainly concerned with the last issue. We focus here on money metric measures of poverty, or what is known as income or consumption poverty, and adopt the $1 a day and $2 a day poverty lines advocated by the World Bank. These choices are not of course free from controversy, but our aim here is to highlight the measurement and methodological problems associated with the prevailing practices regarding the third set of issues.

The purpose of the paper is two-folds. First, it provides poverty estimates for low-income countries, consistent with national accounts statistics and hence comparable over time and across countries. We argue that such consistent estimates are essential for the study of long term trends in poverty as well as for the analysis of the relationship between poverty and other macroeconomic variables in cross country empirical studies. The existing data on poverty by the World Bank fail to satisfy the required consistency tests. For example, as we shall show in this paper, the existing estimates, compared to the national accounts consistent estimates, appear to systematically underestimate poverty in the poorest of Least Developed Countries (LDCs).

The second task of the paper is to provide estimates of poverty in the LDCs where reliable data on income distribution do not exist. The method used is to decompose the variations in absolute poverty into mean expenditure and distributional components, and to extrapolate expected poverty for the LDCs on the basis of their mean per capita consumption expenditure. We also provide confidence intervals for our poverty estimates. The precision of the poverty estimates is measured by the standard error of the mean predicted value, which also indicates the significance of independent variations in income distribution across the countries and over time for poverty. We focus on poverty gap and headcount measures of poverty, and consider the one-dollar and two-dollar per day (in 1985 ppp) absolute poverty lines advocated by the World Bank.

The two tasks set out in the above paragraphs are quite distinct. The first task relates to the adoption of appropriate estimation methods for poverty – appropriate from the point of view of cross-country and time consistency – in the case of countries where income distribution data are available. The second and separate task is to enquire into the possibility of estimating poverty measures, with an acceptable degree of precision, for low-income countries where distribution data are not available. This is clearly predicated upon the availability of a consistent data set for a reasonably large sample of countries. Nevertheless, the two tasks are based on distinct estimation methods and rationales, and their results should stand or fall on their own merits.

Since the first task can be best treated in the context of the discussion of data in later sections, in the next section we shall start with examining some of the underlying assumptions for the possibility of decomposing poverty measures. This is followed by a discussion of data and estimation methods in Section 3. In Sections 4 and 5 we present new national accounts consistent estimates of headcount poverty and poverty gap for the LDCs. Section 6 deals with the validation of the results and compares the properties of the new estimates with the existing estimates. Section 7 examines the implications of our estimates for the recent debate on poverty and economic growth, and concluding remarks are made in Section 8.

2. Scale and Distributional Elements in Poverty Change

In order to get a better understanding of the underlying assumptions of the estimation method adopted here, it would be helpful to consider the two polar cases of poverty reduction shown in Chart 1. In this Chart it is assumed that income distribution takes a parametric form, with u the mean of the distribution, and S, a vector representing shape parameters of the density function. Panel (a) in the Chart depicts a situation where, for a given poverty line z, absolute poverty reduction is taking place purely due to scale effects. The polar opposite is shown in panel (b), where the mean of the distribution remains constant and poverty reduction takes a purely redistributional form. Of course these two polar cases are only theoretical possibilities -- in reality poverty differences across countries, or their changes over time, are generated by combined and often interdependent effects of the two. It should be also noted that in many theoretical distribution functions, e.g., Pareto distribution, the scale and distributional effects are not separable.

An important assumption, necessary for our decomposition exercise, is therefore that the distribution function can be written as a function of the mean and a set of shape parameters. This is satisfied in a number of popular distributions such as the Normal, the Log-normal, and Logistic distributions. In other words, for poverty line z, the cumulative density function for country i can be written as:

$$F_i(z) = F(u_i, S_i; \Sigma, z) \qquad \text{(Eq. 1)}$$

Where u_i is the mean of the distribution, S_i is a shape parameter that captures the distributional influences on absolute poverty, and Σ is a vector of other shape parameters, which are either common across the countries or if different do not affect the poverty measure. As u_i and S_i vary across countries or over time, therefore, this generates a family of S-shaped curves which, for given poverty line z, produce the poverty measure for different countries or times.

$F_i(z)$ in equation 1 is the headcount poverty measure for country i with mean and shape parameters u_i and S_i. In empirical work, this is approximated by P_i, the proportion of population with income below poverty line z, and hence $F_i(z) = P_i + \omega_i$, where ω_i is a white noise error term. Hence:

$$P_i + \omega_i = F(u_i, S_i; \Sigma, z) \qquad \text{(Eq. 2)}$$

The next set of assumptions regard the nature of the shape parameter S, and its relation to the mean of distribution u.[1] One of the most celebrated hypotheses in the literature, that related to the Kuznets curve, maintains an inverted-U shape relationship between income distribution and per capita income (Kuznets, 1955).[2] Kuznets hypothesis, however, refers to income distribution in general and may not necessarily apply to the relationship between u_i and S_i which is only concerned with the shape parameter at the lower tail of the distribution. Furthermore, since we are focusing on a limited range of very low-income countries, any

[1] For ease of exposition here we assume a single shape parameter, but what follows also applies to the cases where S is assumed to be a vector of shape parameters.

[2] For a review of the empirical literature on Kuznets hypothesis see, e.g., Fields (1989, 1991) and Anand and Kanbur (1993).

possible Kuznets effects are likely to be monotonic rather than U shaped. In any event, to account for possible Kuznets effects for our set of low income countries we assume the following general functional form for S_i:

$$S_i = h(u_i) + \varepsilon_i$$

Where ε_i is a white noise error term, assumed to be independent of u_i.

Substituting in equation 2 we get:

$$P_i + \omega_i = F(u_{i,} h(u_i) + \varepsilon_i ; \Sigma, z) = F(g(u_{i,} \varepsilon_i))$$

where the fixed parameters such as z and Σ are absorbed in function g. Applying the inverse function F^{-1} to both sides of this equation we get:

$$F^{-1}(P_i + \omega_i) = g(u_{i,} \varepsilon_i) \qquad \text{(Eq. 3)}$$

Expanding both sides of equation 3 by Taylor series expansion around P_i for the left and 0 for the right hand side, and taking all the terms with ω_i and ε_i to the right hand side, the equation can be approximated by a polynomial in u_i as:

$$F^{-1}(P_i) = \alpha + \beta_1 u_i + \beta_2 u_i^2 + \beta_3 u_i^3 + \ldots + \nu_i \qquad \text{(Eq. 4)}$$

Where ν_i is a composite error term with mean zero and variance which is a function of u_i. Assuming an appropriate S shaped functional form F, the parameters of this equation can be consistently estimated by OLS, and standard errors can be adjusted for possible heteroskedasticity in ν_i. The appropriate functional form for F, the length of the polynomial in u_i, and the structure of the variance of ν_i, can be of course only decided by the data. We applied various popular functional forms such as cumulative normal, log-normal, and logistic distributions, and the best fit was achieved by the logistic function. In the case of the logistic function the above simplifies to:

$$\text{Log}(P_i/(1\text{-}Pi)) = \alpha + \beta_1 u_i + \beta_2 u_i^2 + \beta_3 u_i^3 + \ldots + \nu_i \qquad \text{(Eq.5)}$$

3. Data and Estimation

To measure poverty we need data on distribution of income or consumption, as well as a scale factor, namely the mean income or consumption. The World Bank provides two relatively large data sets based on household expenditure and income surveys on its web site. One is the data set used by Chen and Ravallion (2000), largely based on World Bank's Living Standard Measurement Surveys (LSMS), which has recently become available on the World Bank's web site. The second data set is the Deininger and Squire (1996) data set, which is also available on the World Bank's web site.[3] Our main data source is the former source of data, but we have complemented this data with a few extra observations from the Deininger and Squire dataset (mainly for the 1960s and 1970s decades). The list of sample countries and observations is shown in Table 1. The 92 observations listed in the table are chosen according to the following criteria.

First we have only chosen countries for which data on the distribution of expenditure are available, excluding countries with only income distribution data. Household consumption is arguably a better indicator of long term well being as compared to income. It is also known that the data on household income distribution in developing countries are much less reliable than the consumption data. Furthermore, the mixing of income and consumption data, which is the normal practice in World Bank estimates of poverty, can lead to incompatible estimates for inter-country comparisons (see, e.g., Atkinson and Brandolini, 2001). The exclusion of countries where data on distribution of consumption are not available leaves out most of the Latin American countries. Since most of the low-income countries which constitute the LDCs are located in Africa and Asia, we have altogether omitted the Latin American countries. This increases the homogeneity of our sample countries which is essential for our analysis.[4]

The World Bank databank also provides estimates of headcount poverty (for \$1 and \$2 poverty lines) for our sample countries. The poverty measures supplied by the World Bank, however, suffer from certain deficiencies which make them inappropriate for our estimation purposes. Firstly, as already pointed out the World Bank measures are based on a mix of consumption and income distribution data for different countries which raises questions

[3] See, World Bank (2001) and Deininger and Squire (1996).

[4] We have also excluded South Africa, Zimbabwe and Namibia from the sample, though for these countries data on distribution of consumption expenditure are available. The reason for excluding these countries is that they are clear outliers, i.e., poverty and income distribution in these countries is clearly very different from other countries in the sample.

regarding comparability of the poverty measures for different countries. More importantly, however, the World Bank estimates are based on average consumption or income from national surveys, which are often highly inconsistent with the national accounts data, both in level terms and in relation to trends.

This can be seen from data on per capita consumption in 1985 ppp exchange rates, based on national accounts and survey means for sample observations shown in Table 1. For example in countries such as Tanzania (1991), Ethiopia (1981.1995), and Mali (1989), average consumption figures according to the World Bank's household budget surveys are between two to nearly three times higher than the national accounts estimates. On the other hand, in countries such as Bangladesh, India, Indonesia, Pakistan, and Thailand, the household survey estimates are between 50 to over 100 per cent lower than the national accounts consumption data. The same glaring inconsistency is shown in consumption trends over time. For example, according to the household survey data average consumption increased by over 17 per cent in Ethiopia between 1981 and 1995. According to the national accounts data, however, this variable fell by over 13 per cent between these two years. In Bangladesh between 1984 and 1991, according to household surveys average consumption fell by close to 7 per cent, but the national accounts data indicate a growth of average consumption of over 13 per cent in the same period.

The inconsistency between the household survey results and the national accounts has been discussed in the literature (see, e.g., Hamner, et al. 1997, Bhalla 2000, Pyatt 2000, Ravallion 2000, 2001, and Deaton 2000). The implications of the large discrepancies between the two sources for empirical work, however, have not been often fully recognized. For example, the results of econometric work on poverty and growth, where poverty estimates are based on household survey measurements and growth figures are based on national accounts estimates can be very misleading. Growth elasticity of poverty estimates based on this type of mixing data are also highly suspect – as, relative to national accounts the average consumption in household surveys seem to systematically overestimate consumption in poor African countries, and underestimate it in relatively richer Asian countries (e.g., Thailand, Pakistan, India, Bangladesh, etc.). Because of this discrepancy between the different regions or income groups, the usual explanations put forward in the literature to account for the lack of consistency between the two data-sources are also incomplete.[5]

The difference between average consumption figures based on household surveys and national accounts is not of course unexpected. The two figures are indeed even conceptually different. For example the national accounts consumption data include current spending by unincorporated businesses and non-profit organizations, which are excluded from the household survey means. The question is whether such differences exert significant and systematic effects in cross-country comparisons of poverty. In a recent paper, Ravallion (2000) has compared the national accounts and survey estimates of average consumption and income for a large sample of countries and has concluded that the estimates of average consumption expenditure in the two sources are not significantly different. Ravallion's test is based on the null hypothesis that the ratio of survey average consumption to the national accounts averages has a mean that is not significantly different from 1. He uses a standard t-test for this purpose. Though Ravallion (2000) does not specify the names of the sample countries used in this test, we have managed to replicate the test by using a sample of 84 observations on which the World Bank databank provides average consumption expenditure from household surveys. In row I of Table 2 we have replicated the t-test conducted by Ravallion for the null hypothesis of the mean of the survey / NA consumption ratio being equal to 1. The Table also shows the t-statistic for a range of possible alternatives ranging from 0.0 to 1.5. As pointed out by Ravallion (2000), this test does not reject the hypothesis of mean ratio being equal 1, and seems to have a high power against the alternatives listed in the table.

This test, however, is very sensitive to the order in which the two variables are considered as well as the implicit assumptions about the statistical dependence of the two series. To see this more clearly, we have inverted the consumption ratio reported by Ravallion – that is, we have calculated the NA / survey consumption ratio – and applied the same t-test to the inverted series. The results are reported in Row II of Table 2. As can be seen, for the inverted series the hypothesis of the mean ratio being equal to 1 is strongly rejected.[6] Since there is no a-

[5] In the literature (e.g., Dutt 1999, Ravallion 2001) it is mainly attempted to explain the likely reasons why in a country like India household survey data may underestimate the level and growth of consumption relative to national accounts estimates. As seen above, however, there are countries where the reverse is true.

[6] The reason for this phenomenon could be lack of independence of the two series. Plotting the consumption ratio variable against per capita private consumption one can clearly observe a systematic trend. Since the mean of trended variables is very sensitive to the particular observations chosen, one difference between the above test

priori reason why we should choose one series rather than its inverse to conduct the test, our results cannot support the hypothesis that the two series have the same mean. Under these circumstances the correct procedure would be to test the difference between the means of the two series, which is neutral to the order adopted. This also allows taking into account the possible lack of statistical independence between the two series. This is done in Row III of Table 2, under three separate assumptions; namely, (a)- pooled sample, (b)- non-independent samples, and (c)- independent samples. As can be seen, under the first two assumptions the hypothesis of equality between the two means is rejected, and only under option (c), that is, independent samples, the null hypothesis of mean difference being zero is not rejected. The power of this test, particularly under assumption (c), however, is extremely low. As shown in the last row of Table 2, the possible mean difference between the two series, which cannot be rejected by the t-test, ranges from –6.3% to 62.7% of per capita consumption in the country with lowest consumption in the sample.

The discrepancy in average consumption between the household survey and national accounts data, apart from definitional discrepancies between the two concepts, is due to possible errors in both sources of data.[7] Which of the two sources is more appropriate for poverty measurement depends on the nature of study concerned. If the purpose of the study is to compare poverty in a number of countries and time periods, then clearly the household survey data on average consumption is less reliable. What crucially matters for such comparative work is the consistency of data compilation methods across countries and over time. Household consumption surveys conducted at distant points in time and across countries, with possibly different methodologies, sample designs, and responses, are not particularly reliable indicators or scales or trends, especially when they exhibit average consumption or incomes that are highly divergent from national account estimates. Unless calibrated by external

---

and that conducted by Ravallion (2000) can be due to the difference in samples. Another difference between the two tests may be that we use national accounts consumption data, based on Penn World Tables, while Ravallion (2000) may be based on new ppp estimates by the World Bank.

[7] One potentially important source of discrepancy between the two consumption series, which came to my attention only after completing this work, can be the difference in the PPP exchange rates used. The World Bank has recently changed the base year from 1985 to 1993, and according to them the $1 and $2 poverty lines have correspondingly changed to $1.08 and $2.15 in 1993 prices. However, the change of the base year, if correctly done, should not make any difference to the measurements. As the final year of the Summers and Heston's dataset on ppp exchange rates is 1992, it is difficult to check the consistency of the new World Bank figures with the old ones. It appears, however, that apart from changing the base year, the World Bank 1993 ppp rates are also re-estimates of some of the earlier measures in Penn World Tables version 5.6 (see, e.g., Chen and Ravallion 2000). Since there is no official documentation on this and the data are not available publicly, we have used the original Penn World Tables version 5.6 estimates to calculate per capita consumption in 1985 ppp exchange rates.

information, averages or scale factors are unlikely to be comparable across the different household expenditure surveys – even when they are reliable information sources regarding the distribution of income or consumption. Household expenditure surveys are at best good indicators of distribution of income or expenditure, but can be highly unreliable with regard to averages. Under these circumstances, average income or consumption in national accounts estimates, despite their shortcomings, furnish a more consistent and comparable set of scale variables than those generated by the household surveys.[8]

In this paper we have therefore based our poverty estimates on national accounts scale variables. This generates poverty estimates that are consistent with the national accounts. In order to estimate national accounts consistent poverty measures we still need to combine the distribution information provided in household surveys with the scale variables from the national accounts. The extent to which the scale errors in household surveys affect the accuracy of distribution data as well, depends on whether the scale errors arise because of under- (over-) reporting of income in particular deciles or they uniformly affect all income groups, or whether they are due to the problems with survey sample design.[9] In any event, since the scale effects are likely to be more important than distribution effects in cross-country and time comparisons of poverty (particularly as we are mainly concerned with the lower end of the distribution), the likely errors involved in using the distribution data from household surveys may not be as significant as those arising from scale effects. Using the national accounts information for the scale effects and the household budgets for the distribution effects is the only available option for deriving national accounts consistent poverty estimates, while at the same time being least sensitive to the measurement errors in household budget data. We have adopted this method also because one of the aims of the paper is to estimate expected poverty for countries where household budget surveys do not exist. As pointed out above, data consistency is of utmost importance for this type of exercise. We shall compare the properties of our poverty estimates with the World Bank estimates based on household survey averages.

[8] This of course does not mean that national accounts estimates are very accurate. Indeed the errors involved in national accounts estimates of consumption, particularly in LDCs, can be very substantial, as these are usually estimated as residuals. But nevertheless the national accounts figures are more consistent over time and across countries than the survey averages.

[9] See, Atkinson and Brandolini (2001) on the problems associated with intercountry comparison of distribution data based on secondary sources.

Chart 2 (panels a and b) plots the new national accounts consistent poverty estimates against average consumption for all the countries and years for the $1 a day and $2 a day poverty lines. Countries included in the $1 poverty line graph have per capita income below $1000 a year (in 1985 ppp dollars). Below this per capita income level headcount poverty becomes negligible. The number of observations for the $1 poverty line are, therefore, less than those estimated for $2 poverty line.[10] A logistic curve is fitted to the observations in both panels. The estimation method for this curve, which we may refer to it as the poverty curve, is discussed below. The variation of the poverty measures around the 'poverty curves' are remarkably low – indicating that independent variations in income distribution explain a small part of variations in poverty across our sample of low income countries and over time.[11] In order to compare the new poverty estimates with the World Bank poverty measures, based on household survey scale factors, we have plotted the two series against per capita consumption in Chart 3.[12] The same sample of countries and the same years are included in both series in this chart.[13] As can be seen, the World Bank estimates show much higher variations around the trend, and show much lower slopes in the case of both the $1 and $2 poverty measures (panels a and b). The much larger variation of the World Bank series is not unexpected, because those series are generated by using a different scale factor from that depicted on the horizontal axis of Chart 3. The Chart, however, helps to highlight the dangers of mixing incompatible data sources in measuring poverty trends – which is not uncommon in the literature (see, e.g., Chen *et al*., 1994, Ravallion and Chen 1997, Chen and Ravallion, 2000).[14] What is also clear is that, at least for the low income countries considered here, the World Bank estimates systematically underestimate poverty in poorer countries and overestimate it

[10] There are 58 observations for the $1 line and 90 observations for the $2 line. The number of observations for the $2 poverty line is less than the number of observations in Table 1 because per capita income in Ethiopia is too low to estimate precise headcount poverty the two observations listed in the table for Ethiopia. These two observations have therefore been dropped.

[11] This of course does not imply that income distribution has no significant effect on poverty. Such effects are however likely to be mediated via scale or growth effects, and are too complex to be identified in statistical models of this type.

[12] In order to be consistent with the World Bank estimates we have used World Bank's POVCAL program to estimate the new poverty measures.

[13] There are fewer observations in Chart 4 as compared to Chart 3, because the former only contains observations for which both World Bank estimates and national accounts based estimates of poverty are available.

[14] For example, according to Chen and Ravallion (2000, p.8), 'If there is only one survey for a country, then we estimate measures for each reference year by applying the growth rate in real private consumption per person form the national accounts to the survey mean – assuming in other words that the Lorenz curve for that country does not change'. The problem here is not the assumption of constancy of the Lorenz curve, which is a permissible assumption given the lack of data. The main problem is the mixing of poverty measures and trends with totally different and incompatible scale variables.

for the richer ones. The substantial differences between the new results and the World Bank results are of course solely due to the differences in the scale factors used, as both series use the same distributions.

4. Headcount poverty estimates in the LDCs

The very low standard errors of the fitted curves to the new poverty measures indicate that one may be able to estimate, with a high degree of precision, the expected value of poverty in low income LDCs for which income distribution data are not available. Before attempting this, we need to further explore the possibility of introducing additional explanatory factors which may further reduce the standard errors of the fitted curves. For example, because of structural changes and different policy regimes over time, the relationship between poverty and average consumption may have changed. To cater for this, we have introduced a time-dummy variable D90 which distinguishes the 1990s decade from the earlier decades.[15] Similar structural differences may affect the relationship between poverty and average consumption across regions as diverse as Asia and sub-Saharan Africa. For this reason we have also added a REGION dummy variable to the regression lines. Regression results are shown in Tables 3 and 4. The dependent variable is the logistic transformation of the new headcount poverty measure for the \$1 and \$2 poverty lines, discussed above. Various other functional forms were tried, but only the preferred logistic model results are shown in the Tables.

Table 3 shows the results for the \$1 poverty line for various specifications. In addition to the REGION and time dummy variables we included various powers of consumption in order to determine the most appropriate form of the polynomial function specified in equation 5 above. Only the first and second powers were significant and the best fit was a polynomial of degree two as shown in Table 3. Regression II in Table 3 corresponds to the fitted line in Chart 3a. The R^2 of close to 0.95 reflects the close fit of this curve as observed in the Chart. With the addition of the time and region dummies in regression III, adjusted R^2 increases to over 0.96. The negative and significant regional dummy variable indicates the adverse structural features of the sub-Saharan African countries, which imply a more unequal

[15] The number of observations for the 1960s and the 1970s decades are too few to distinguish the four decades separately.

distribution of income than in Asia. The time-dummy in regression model III is not statistically significant. We have used equation IV in Table 3 for predicting the expected value of poverty ($1 line) in the LDCs.

Table 4 shows the regression results for the $2 poverty line. As in the $1 case, the best fit was achieved by the logistic function, as compared to the cumulative normal and log-normal functions. Similarly, a polynomial of power two in per capita consumption turned out to be most appropriate. As shown in models III and IV in Table 4, the addition of the regional and time dummies does not improve the fit of the model. This is not an unexpected result, as in most low income countries in our sample the majority of the population fall below the $2 line, and hence distributional changes over a wide range of the incomes (below the poverty line) do not affect the headcount poverty measure. We have therefore used equation II in Table 4 for predicting the expected value of absolute poverty (below $2) for the LDCs.

The close fit of the logistic regression lines implies that we may be able to predict the expected value of poverty for countries where income distribution data are not available, with a fair degree of accuracy. We have used the average figures for per capita private consumption for 1995-99 to estimate headcount poverty for the LDCs for this period based on the above regressions. Real consumption figures in international dollars (1985 ppp) are based on Penn World Tables for the 1965-92 period, and on World Bank, WDI (2001) for the rest of the period.[16] The results are shown in Table 5, which also shows the 95 per cent confidence interval for the poverty estimates. It is significant to note that for the majority of the LDCs, per capita consumption for the major part of the population falls below the $1 and $2 a day poverty lines. We may refer to this as a situation 'generalized poverty', which is quite distinct from normal poverty observed in more developed countries. Indeed, its is unlikely that the close fit of the poverty curve to the observations can also apply to situations other than the generalized poverty situation (see, section 7).

5. Poverty Gap and the Average Consumption of the Poor

The same decomposition procedure applied to the headcount poverty measure above, can be also applied to other poverty measures such as the poverty gap. Poverty gap is defined as the difference between the mean income (consumption) of the poor and poverty line, expressed as

[16] Post-1992 figures are estimated by applying growth rates of real per capita consumption from the World Bank WDI databank to the Penn World Table ppp figures.

percentage of the poverty line. It is a simple indicator of income distribution amongst the poor. However, as soon as one fixes the value of the absolute poverty line, changes in poverty gap can take place as a result of the combination of variations in income distribution and the overall mean income. It can be shown that, similar to the headcount measure, poverty gap can be also approximated by a polynomial function of mean consumption (of total population) and distributional components as set out in equation 4 in Section B. As the poverty gap index varies between zero and one, an S shaped curve, similar to the one fitted to the headcount measure would be appropriate. Again, depending on the goodness of fit of the model to the data, one may be able to estimate more or less precise measures of poverty gap for countries where income distribution data are not available on the basis of the regression results.

Since we have fixed absolute poverty lines at \$1 and \$2, it may be more informative if we report estimates of average consumption of the poor rather than the poverty gap. Having estimates of the average consumption of the poor, one can calculate poverty gap by a simple transformation of the average consumption figures. The information on the average consumption of the poor can also serve a useful purpose by making it possible to estimate the amount of income transfers necessary to raise the consumption of the poor above the poverty line. We have therefore estimated the following regression equation:

$$F^{-1}(CP_i) = \alpha + \beta_1 u_i + \beta_2 u_i^2 + \beta_3 u_i^3 + \ldots + \nu_i \qquad (6)$$

Where CP is average consumption of the poor, u is average consumption of total population, and F is an appropriate S shaped functional form. As before, the polynomial in u characterizes the scale effect on the average consumption of the poor, and the residual ν the independent distributional effects. We have calculated the average consumption of the poor for the same number of countries and years as above, using World Bank's distribution data and the POVCAL programme used by the World Bank. The only difference between our measures of poverty gap and the World Bank's is that we use overall per capita consumption data which are consistent with national accounts in contrast to average survey results. The mean annual consumption of the poor for the observations in our sample is plotted against average annual per capita consumption of the whole population (both measured in 1985 ppp) in Chart 4a for the \$1 poverty line and Chart 4b for the \$2 line. The Charts also show the fitted logistic curve to the two sets of data. The regression results for equation 6 are shown in Table 6 (for the \$1 line) and Table 7 (for the \$2 line). As for the headcount regressions, in addition to the polynomial in overall consumption, we have also tried the time and region dummies discussed above. Amongst the various S-shaped curves, such as cumulative normal, logistic, and log-normal, the cumulative logistic curve attained the best fit for both regressions.

As shown in Tables 6 and 7, the time dummy variable was not significant in any of the regressions, but the regional dummy had a positive and significant coefficient in both, indicating that for given level of overall per capita consumption, the average consumption of the poor in Asian countries is higher than Africa. In the case of the \$1 regression line a 1^{st}-degree polynomial in consumption achieves the best fit, and in the case of the \$2 line a 2^{nd}-degree polynomial fits best. In both equations more than 90 per cent of the variations in the consumption of the poor is explained by the variations in average consumption and the regional dummy variable. Hence, except for the distributional effects associated with the regional dummy variable and those associated with the variations in mean consumption, income distribution plays a relatively small independent role in explaining the variations in poverty gap for the sample countries and years. This of course does not mean that the distribution of income or assets do not matter for the consumption of the poor. They can and do matter critically through their influence on growth.

We next compare our poverty gap measures with those of the World Bank. Charts 5a and 5b show the scatter plot of the new estimates of the average consumption of the poor against per capita consumption, compared to the consumption figures calculated on the basis of the World Bank's poverty gap estimates for the two poverty lines. As can be seen, the World Bank estimates seem to systematically underestimate average consumption of the poor in poorer countries, and overestimate it in the case of the richer ones. As pointed out before, the only difference between the new estimates and the World Bank ones is that they use different scale variables, but the income distribution data for the two are the same. In particular in the case of the \$1 poverty line, World Bank's estimates of the average consumption of the poor for a number of lower income countries is on average the same as for countries that have per capita overall consumption of two to three times higher than the former (Chart 5a). This is of course purely because of the difference between the survey and national accounts consumption averages.

Given the relatively close fit of the data in the regressions in Tables 6 and 7, we may be able to estimate relatively reliable measures of expected consumption of the poor in LDCs where income distribution data are not available. We have used regression IV in both Tables to estimate expected consumption of the poor for a number of LDCs for the \$1 and \$2 dollar poverty lines. The average per capita consumption for 1995-99 is used to calculate expected consumption of the poor in that period. The results for daily consumption of the poor measured in 1985 ppp dollars are shown in Tables 8 for the \$1 and \$2 poverty lines. The Tables also show the 95 per cent confidence intervals for the expected consumption of the poor for 1995.

6. Validation of the results

The choice of national accounts estimates of average consumption in this paper has been based on the argument that the average income or consumption figures based on national accounts data furnish a better set of scale variables for cross-country comparison of poverty, as compared to the survey averages. In the next section we shall discuss in what sense the term poverty should be used in this context. In this section we shall report a number of validation tests for our results and further compare the properties of the new estimates with the World Bank estimates based on survey averages. Given the two tasks of this paper mentioned at the outset, our validation tests are accordingly grouped into two types. The first one is to consider how realistic our estimation results are for countries where distribution data are not available. The second task is to consider how valid our poverty estimates are as compared to the World Bank estimates for countries where distribution data are available. We start with the first validation test.

To check the plausibility of our estimates of poverty for countries where income distribution data are not available, it would be instructive to examine the accuracy of the estimates for countries where such data are available, so that estimates can be compared with actual figures. This is done by the following procedure: we drop individual observations from the sample one at a time, estimate our regressions with the reduced sample, and then compare the estimated poverty from the regression for the missing observation against the actual poverty measure. For each observation we get one such prediction error on the basis of which we can judge the precision of our estimates. This is done for the four regressions that have formed the basis of our four expected poverty measures reported above. We have plotted the prediction errors calculated in this way in Chart 6, for headcount poverty, and Chart 7, for the average consumption of the poor. We have also reported the mean absolute error of our estimates in Table 9. As can be seen, the observations are clustered very close to the 45 degree lines in all the charts, indicating that the errors are reasonably small – a fact that is also supported by relatively small mean absolute errors in Table 9. Table 9 also reports mean absolute error of the World Bank estimates, compared to our new (actual) estimates. The substantially larger size of the mean absolute error for the World Bank estimates in all the cases is worthy of note. It means that, under the maintained hypothesis that the new estimates are the preferred ones, the World Bank estimates of poverty in the case of countries where distribution data are available, are even less reliable than our regression estimates for countries where distribution data are not available. We have not, however, yet formally validated the assumption that the new national accounts consistent estimates are preferred to the World Bank estimates. This is the task of our next validation exercise. Our next validation test, therefore, is to see how the national accounts consistent measures compare to the World Bank estimates in countries where distribution data are available.

There has been a growing literature comparing the merits of national accounts and survey consumption and income averages in measuring poverty (see, e.g., Deaton 2000, and Ravallion 2001). In none of this literature, however, there has been an attempt to test the properties of the poverty measures estimated on the basis of the two scale variables. Our second validation test is precisely to do this. Our argument so far, in preferring the national accounts scale factors, has been based on the accepted fact that unless survey averages are calibrated by external information (e.g., national accounts data), they do not generate reliable averages, even when they contain reliable distribution information. However, if this argument is correct we should be able to test this on the basis of the available external information on poverty that is derived independent of the two poverty estimates being compared (e.g., information on malnutrition etc.). One such external information is the data on the percentage of undernourished population produced by the FAO. The second external indicator is the UNDP's human development indicator (HDI). As both the FAO and the UNDP data are available for a relatively large number of sample countries, we shall attempt to test the new estimates against the World Bank estimates using these two indicators.

The test consists of comparing the explanatory power of the two poverty measures in relation to the FAO measures of undernourished population, and the UNDP measure of HDI. We have regressed the FAO series (percentage of undernourished population) on our new poverty measures and the World Bank measures, with the results reported in Table 10. A similar regression is run using the HDI measure of the UNDP, with the results reported in Table 11. Two sets of results are reported in each table, corresponding to the two measures of headcount poverty reported above.[17] The number of observations in the sample varies between different equations depending on the availability of data common to the three sources of data. As can be seen from Table 10 and 11, when both poverty measures are included in the regression, in all the four models, the new estimates show highly significant coefficients with the correct sign, but the World Bank poverty measures have insignificant coefficients in all the cases except one. Once we drop the World Bank measures from the regression the adjusted R^2 in fact improves in three equations out of four, and with the exclusion of the new estimates the explanatory power of the regression is drastically reduced. Any of the standard statistical tests of variable selection applied to these regressions will clearly reject the World Bank estimates in favour of the new estimates. These results indicate that the new estimates contain almost all the useful information that the World Bank estimates may contain, but the information content of the World Bank estimates of poverty are rather low.[18] Since we can also show that in most regressions reported in Tables 10 and 11 the coefficient of the World Bank poverty variable is significantly different from those of the new estimates, the use of the World Bank data in cross country analysis, when it does generate significant results, can be misleading.

In the light of the regression results in Tables 10 and 11, we can further examine the implications of the mean absolute errors reported in Table 9. The fact that the mean absolute error of the World Bank estimates is many times larger than the mean absolute error of our expected poverty measures based on regression results, can mean that the information content of the World Bank data on poverty is even less than our estimates for countries where distribution data are not available. To test this more directly, we have re-run the above regressions, this time using our poverty measures based on logistic regressions (used in our first validation test reported above) rather than the actual new poverty estimates. The results, reported in Tables 12 and 13, indicate that even our expected poverty estimates that do not

[17] The same tests were applied to the other two poverty measures, namely, the average consumption of the poor for the \$1 and \$2 poverty lines. But since the results are not different form the headcount poverty results, they are not reported here.

[18] This is of course in relation to the HDI and the FAO poverty measures, which themselves can be subject to serious errors. For a critique of the FAO's nutrition measure see, e.g. Svedberg (1999).

utilize the actual income distribution information for the sample countries can be better indicators of poverty than the World Bank estimates. [19]

7. The relationship between poverty and Growth

The relationship between economic growth and poverty reduction has been subject to a good deal of controversy and debate in recent years. The issues have been hotly contested amongst academics, policy makers, the NGOs and the popular presses of various hues. A recent summing up of this debate has tried to explain the apparent lack of understanding between the incumbents on the basis of differences in perspectives, between on the one hand economists and responsible policy makers (referred to as the finance ministry tendency), and on the other hand the NGOs and the interested members of the public (the civil society tendencies) (Kanbur, 2001). The reality, however, is much more complex. There seems to be a great deal of confusion on this issue even amongst the academic and policy-making community.

A related issue, which highlights some of the underlying problems in the growth/poverty debate is what in the policy literature, mostly those emanating from the World Bank's research department, is referred to as the growth elasticity of poverty reduction. The term growth elasticity of poverty reduction implicitly assumes that there is a stable relationship between growth of per capita income and poverty reduction. Most of the elasticity estimates are based on cross-country regressions of the percentage change in some measure of poverty (e.g., the headcount measure) against the percentage change of per capita consumption or GDP, with possibly some trend variables. Thus the results are generally presented as a fixed or single valued elasticity for a large heterogeneous sample of countries for which income distribution data are available at different points of time. These results, however, vary substantially, depending on the particular sample of countries chosen, and the poverty lines and poverty measures adopted.

For example Ravallion and Chen (1997) provide headcount poverty elasticities ranging from –0.53 to –3.12, for various poverty lines and samples, based on consumption averages from

[19] The above of course depends on the assumption that the FAO and UNDP data are generated independent of the two poverty measures being examined. These results need to be further examined using other independent sources of information on poverty.

household surveys. With similar methodologies UNECA (1999 and 2001) provide measures of income growth elasticity of headcount poverty for Africa of –0.92 and -0.85. Ravallion et al (1991) on the other hand calculate headcount elasticities of –2.2 for the developing countries and –1.5 for sub-Saharan Africa, based on per capita consumption growth. And the list goes on. The question that arises is what meaning can one give to these aggregate elasticity estimates? Under what conditions can one assume stable poverty reduction elasticities and what are the reasons for the clearly unstable elasticity measures? In answering these questions one also touches on some the important issues in the growth/poverty reduction debate.

To examine the conditions under which it may be plausible to assume a stable relationship between growth and poverty reduction, it would be helpful to distinguish between a situation of generalized poverty and what one may refer to as the 'normal' poverty situation. The difference between the two is depicted in Chart 8, which shows two economies A and B with the same distribution of income but considerably different average per capita incomes. The same international poverty line, Z (say $1 a day), generates totally different estimates of headcount poverty in the two cases. Case A in the chart, i.e., the normal poverty situation, is where poverty is confined to the tail of the distribution. In case B, the generalized poverty situation, the majority of the population fall below the poverty line. As shown in the previous section, case B is typical of the LDC economies with reference to the $1 and $2 a day international poverty lines.

In case A, economic growth is neither necessary nor sufficient for poverty reduction. It is not necessary because the economy already has sufficient resources to introduce poverty alleviation programmes. It is not sufficient, because no matter how high an economy's per capita income level may be, there will always be individuals or households who, because of their own special circumstances or because of sectoral shifts or cyclical fluctuations in the economy, fall below the poverty line. Poverty reduction in these circumstances depends on social and political processes and necessarily involves a redistribution of income. The introduction of different types of social welfare system in the European countries after the Second World War is an example this type of poverty reduction. The differences in observed rates of extreme poverty in different European countries in the post-war period is explained more by their social and political institutions than their per capita income levels. High rates of economic growth may ease the acceptance of redistribution policies, but there is no empirical relationship linking high growth rates to the introduction of more adequate welfare systems in these countries.

In case A, or in a 'normal' poverty situation, therefore, the term growth elasticity of poverty reduction is not a very meaningful concept – at least for the case of absolute poverty which is the main concern here. In Case B, the generalized poverty case, however, the situation is very different. Since the majority of the population in this case fall below the poverty line, growth and poverty reduction are necessarily linked. Redistribution can play some direct role in alleviating the worst aspects of poverty even in such economies, but reduction of poverty of the type charachterized by the absolute poverty line Z can be achieved on a non-negligible scale only through economic growth. This does not mean that redistribution of income and assets in such economies do not play an important role in poverty reduction, but that such a role, in order to be significant under the conditions of generalized poverty, has to be mediated through economic growth. Efficiency enhancing redistribution of assets and incomes are indeed essential for poverty alleviation when there is extreme generalized poverty.

Under the conditions of generalized poverty, economic growth is not only necessary for poverty alleviation on a major scale, but under 'normal' conditions, it can be also sufficient. We shall shortly examine what constitutes 'normal' conditions, but it should be clear that it is only with the existence of such normal conditions or normal patterns that the term growth elasticity of poverty reduction becomes meaningful. Growth elasticity of poverty reduction, therefore, is a plausible concept only under the conditions of generalized poverty and when economies can be assumed to follow similar 'normal' historical patterns of development.

The next question is what are the empirical regularities or historical patterns of growth and poverty reduction, and under what conditions can they justify the notion of growth elasticity of poverty at an aggregate level? In order to address this question we have plotted the $1 and $2 headcount poverty measures for our sample observations against per capita consumption at 1985 ppp exchange rates in Chart 9. The data refers to more than 34 countries over three decades, and if there are any regular pattern between headcount poverty at the two international poverty lines and per capita consumption it should be reflected in this Chart. In order to observe the normal pattern in the historical relationship between the two variables we have dropped some of the clearly outlying countries such as South Africa, Zimbabwe and Namibia, and as pointed out above have confined the sample to only Asian and African developing countries. As can be seen there seems to be a clear relationship between the level of per capita consumption and headcount poverty. The relationship, however, is a highly non-linear one, and very different from the linear or log-linear relationship often assumed in aggregate elasticity estimates.

A number of points need to be emphasized about the relationships between per capita consumption and poverty depicted in Chart 9. One point is that, as the observations are mainly cross-country, with some countries having more than one observation, the pattern should be regarded as a long-term 'normal' relationship between growth and poverty. It is a normal relationship in the sense that according to observed patterns countries emerging out of a situation of generalized poverty are expected to follow these paths in the long-run. For example, an average African LDC where close to 89 per cent of the population live below \$2 a day and where per capita consumption is on average \$1.13 a day at 1985 ppp rates, would be expected to increase its per capita consumption to over \$4 a day in order to achieve headcount poverty of about 20 per cent.[20] This is the, so to speak, necessary condition. The sufficiency condition on the other hand maintains that if an economy with generlized poverty, with close to 89 per cent of the population living below \$2 a day, and with an overall per capita consumption of \$1.13 can grow so that its overall per capita consumption reaches \$4 a day, then this economy is likely to attain poverty rates of about 20 per cent. This is what the 'normal' patterns of economic development according to Chart 9 indicate. However, there are exceptions such as South Africa and Zimbabwe (excluded from the chart), indicating that economic growth may not be sufficient for poverty reduction. But the exceptional historical experiences of countries such as South Africa and Zimbabwe, and the lack of political and economic sustainability of these experiences, also indicates that these may be exceptions that indeed prove the rule. Though there is no guarantee that the future trajectories of growth and poverty reduction will follow the past, it is highly likely that there will be always a strong relationship between the two under the conditions of generalized poverty.

Even though Chart 9 shows a close association between growth and poverty reduction in LDC type economies suffering from generalized poverty, it nevertheless does not support the validity and usefulness of the aggregate elasticity concept often used in the studies of poverty in the LDCs. The highly non-linear shape of the apparent relationships between poverty

[20] Though this statement can be also made in terms of the 'growth elasticity of poverty reduction' terminology, it is important to note that this elasticity depends on the initial level of per capita income as well as on the poverty line chosen, which differs from the fixed elasticity figures normally used in the literature. This point is further elaborated in the text that follows.

reduction and growth indicates that one should be wary of the pitfalls of such aggregate measures. Charts 10 and 11 show the growth elasticities of poverty implicit in the non-linear relationship in Chart 9, for the headcount poverty and the average consumption of the poor respectively, for both the $1 and $2 poverty lines. As can be seen both the marginal response of poverty to growth as well as its elasticity is critically dependent on the poverty line chosen as well as on the level of per capita income or consumption in the country concerned. Considering the point made above about the relevance of growth elasticities for countries with generalized poverty, Chart 10 indicates that for the $1 poverty line such growth elasticities can range from –0.5 to about –3.0, and for the $2 poverty line it can vary between -0.5 and over –2.0, for the range of per capita incomes that fall into the generalized poverty category. Similarly, Chart 11 indicates that the elasticity of the consumption of the poor with respect to the growth of overall per capita consumption can vary between 0.5 and close to 0.75 for both the $1 and $2 poverty lines, for different levels of per capita consumption within the LDC range. This is incidentally in conformity of Kuznet's hypothesis that at the early stages of development, income inequalities tend to increase. Economic growth, nevertheless, reduces poverty in countries suffering from generalized poverty.

8. Concluding Remarks

In this concluding section it may be appropriate to start with spelling out some of the caveats and reservations about the concepts, data, and methods used in this paper. First, one should be careful not to extrapolate poverty on the basis of the above results for consumption ranges beyond the sample. The non-linear relationship between poverty and average consumption makes such extrapolation particularly hazardous. It is also very likely that at higher income levels the statistical models applied would become less precise, as the residuals or the independent income distribution effects can become more prominent.

Secondly, our results should not convey the impression that only growth matters for poverty alleviation and that income distribution plays a minor role. Such an impression results only from a mechanistic and superficial interpretation of the results. As we have emphasized at various places in the paper, under the conditions of generalized poverty income distribution can play a crucial role in poverty alleviation through its growth effects. For example, consider a redistribution of assets and incomes in the agricultural sector, e.g., following a land-reform, that may at the same time result in a rapid growth of productivity and incomes in that sector and in the economy as a whole.[21] The growth of the other sectors of the economy in this process can lead to income distribution outcomes, which may be very different from the initial effect of the land reform. This, however, does not mean that the original redistribution has not played any role in poverty alleviation. Such dynamic effects, however, are too complex to be picked up by statistical analysis of this nature or through simplistic cross-country econometrics exercises based on aggregate ex-post observations. Recent debates on the respective roles of growth and income distribution on poverty alleviation based on this type of exercise, therefore, are likely to remain sterile and unproductive.

Thirdly, despite the fact that in parlance with the existing literature we have referred to the new estimates as poverty indicators, one should be aware of the differences between these measures and the conventional national measures of poverty. The headcount measure of the population living below \$1 or \$2 a day can differ from national poverty measures based on poverty lines defined on the basis of appropriate consumption baskets and prices facing different groups of the population.[22] The \$1 and \$2 poverty lines also may not reflect the intensity of poverty in different countries. This is not just because of the differences in institutions, customs, and the available goods and services, or the differences in the distribution of consumption amongst the poor in different countries. It is also, and possibly more importantly, because of the errors involved in measuring ppp exchange rates relevant to the consumption basket of the poor in each country. As they are, the consumption ppp exchange rates for many poor countries are extrapolated on the basis of available information on other 'similar' countries and hence are not very accurate. Furthermore, even when accurately estimated, they do not reflect the appropriate exchange rates for the consumption basket of the poor.

The real value of the \$1 and \$2 headcount poverty measures is that they provide reasonably comparable information across countries on resources available to the poorest part of the population to sustain their lives. One cannot remain faithful to both this type of internationally comparable notion of poverty, and the nationally defined measures of poverty.

[21] The point here is not whether asset redistribution will lead to growth or not. Even if it has negative growth effects the above argument still holds.

[22] Ravallion et al. (1991), show that the one dollar poverty line is relatively close to the average of official poverty lines in a number of low income countries. The variations around this average are nevertheless still quite substantial.

The problems associated with the World Bank's measures of poverty highlighted in this paper, may have arisen because of their attempt to strike a balance between these two essentially different notions of poverty. However, once one defines internationally comparable poverty lines like the $1 and $2 a day lines, one should be more concerned about the comparability of the measured poverty across countries rather than being close to nationally defined measures of poverty. It is not unlikely that in the case of some countries the new poverty measures estimated in this paper are different from the national measures of poverty. As long as our measures are internationally comparable and consistent, however, this should not be a cause of concern, because internationally comparable absolute poverty measures are meant to serve a different purpose from the national definitions of poverty. An important contribution of internationally comparable poverty measures based on the $1 and $2 poverty lines is to identify low-income countries suffering from extreme 'generalized' poverty. Economic policies for growth and poverty alleviation in such economies are likely to be very different from policies that appear to be effective in the context of economies with a more 'normal' poverty situation.[23]

In this context two issues which can greatly benefit form further research, and are indeed in need of such research, stand out. First is the estimation of more accurate ppp exchange rates for the low-income countries, appropriate for inter-country poverty comparisons. The existing estimates are clearly unsatisfactory. Another area of research which needs serious attention is the reconciliation of the national accounts and survey data on average income and consumption. With poverty alleviation becoming a central international goal for low-income countries, these tasks become particularly urgent as the existing data and methodologies inhibit effective policy and analytical research.

[23] On this point see, UNCTAD (2000, and 2001).

Bibliography

Anand, S. and S.M.R. Kanbur (1993), 'Inequality and Development: A Critique', Journal of Development Economics, vol.41, no.1, pp.19-43.

Atkinson, A.B. and A Brandolini (2001), 'Promise and Pitfalls in the Use of 'Secondary' Data-Sets: Income Inequality in OECD Countries as a Case Study', *Journal of Economic Literature*, vol.39, pp.771-99, September.

Bhalla, S.S. (2000), 'Growth and Poverty in India: myth and reality', mimeo (http://www.oxusresearch.com/economic/asp).

Chen S. and M. Ravallion (2000), 'How did the world's poorest fare in the 1990s?', mimeo, World Bank: Washington D.C.

Chen S., G. Datt and M. Ravallion (2000), 'POVCAL. A Program for Calculating Poverty Measures from Grouped Data', World Bank: Washington D.C.

Chen S., G. Datt and M. Ravallion (1994), 'Is poverty Increasing or Decreasing in the Developing World?', *Review of Income and Wealth*, no.40, pp.359-76.

Deaton A. (2000), 'Counting the world's poor: problems and possible solutions', mimeo, Research Program in Development Studies, Princeton University.

Datt, G. (1999), 'Has poverty in India declined since the Economic Reforms?', *Economic and Political Weekly* no.34, December 11-17.

Deininger, K. and L. Squire (1996), 'A new Data Set Measuring Income Inequality', *World Bank Economic Review*, v.10, no.3, pp.565-91 (data available at: http://www.worldbank.org/ research/growth/dddeisqu.htm).

Fields, G. S. (1989), 'Changes in Poverty and Inequality in Developing Countries', *World Bank Economic Observer*, vol.4, no.2, pp.167-85.

Fields, G. S. (1991), 'Growth and Income Distribution', in G. Psacharopoulos (ed.), *Essays on Poverty, Equity and Growth*, ch.1, pp. 1-52, Pergamon Press: Oxford.

Hamner, L., G. Pyatt and H. White (1997), Poverty in sub-Saharan Africa: what can we learn from the World Bank's Poverty Assessments?', mimeo, Institute of Social Studies: The Hague.

Kanbur, S.M.R (2001), 'Economic policy, distribution and poverty: the nature of disagreements', World Development 29(6).

Kuznets, S. (1955), 'Economic Growth and Income Inequality', *American Economic Review*, vol.45, no.1, pp. 1-28.

Pyatt, G. (2000), 'The distribution of living standards within countries: some reflections on an evolving international data base', mimeo, Institute of Social Studies, The Hague, the Netherlands.

Ravallion M. (2000a), 'Do National Accounts Provide Unbiased Estimates of Survey-based Measures of Living Standards?', mimeo, World Bank, Washington D.C.

Ravallion M. (2000b), 'Should poverty measures be anchored in national accounts?', *Economic and Political Weekly*, August 26-September 2, 2000, pp. 3245-3252.

Ravallion (2001), 'Growth, Inequality and Poverty: Looking Beyond Averages', mimeo, World Bank, Washington D.C.

Ravallion M. and S. Chen (1997), 'What can New Survey Data Tell Us about Recent Changes in Distribution and Poverty?', *World Bank Economic Review*, 11(2), pp.358-82, World Bank: Washington D.C.

Ravallion, M., G. Datt and D. van de Walle (1991) 'Quantifying Absolute Poverty in the Developing World', *Review of Income and Wealth*, no.37, pp.345-361.

Svedberg, P. (1999) "841 million undernourished?" *World Development*, vol. 27, no.12, pp2081-2098

UNCTAD (2000), *Least Developed Countries Report 2000*, UNCTAD: Geneva.

UNCTAD (2001), *Least Developed Countries Report 2001*, UNCTAD: Geneva.

UNECA (1999), *Economic Report on Africa, 1999*, Economic Commission for Africa, E/ECA/CM.24/3, Addis Ababa.

UNECA (2001),

World Bank (2001), *www.worldbank.org/research/povmonitor/index.htm*, World Bank: Washington D.C.

Tabel 1, Survey Based and National Accounts Based per capita Consumption for Sample Observations

			Per capita Consumption					Per capita Consumption	
Obs.	Country	Year of Survey	N.A. based	Survey based	Obs.	Country	Year of Survey	N.A. based	Survey based
1	Algeria	1988	1384.5	1875.4	47	Madagascar	1980	856.1	557.1
2	Algeria	1995	1295.4	1754.8	48	Mali	1989	426.6	852.8
3	Bangladesh	1984	729.6	535.1	49	Mali	1994	353.9	360.8
4	Bangladesh	1985	753.9	586.0	50	Mauritania	1988	567.4	534.4
5	Bangladesh	1988	765.8	518.7	51	Mauritania	1993	680.0	605.9
6	Bangladesh	1991	796.0	498.7	52	Mauritania	1995	642.3	661.1
7	Bangladesh	1995	885.8	613.3	53	Morocco	1985	1330.1	1708.9
8	Burkina Faso	1994	401.7	477.9	54	Morocco	1990	1526.5	2352.4
9	Egypt	1991	1243.5	984.8	55	Mozambique	1996	589.9	588.7
10	Ethiopia	1981	231.8	558.4	56	Nepal	1985	393.1	491.9
11	Ethiopia	1995	228.8	657.8	57	Nepal	1995	489.1	584.4
12	Gambia	1992	623.0	504.7	58	Niger	1992	312.7	523.0
13	Ghana	1987	630.2	854.4	59	Niger	1995	331.1	401.9
14	Ghana	1989	607.5	887.2	60	Nigeria*	1986	564.3	..
15	Ghana*	1992	793.5	..	61	Nigeria*	1992	674.8	..
16	Guinea-Bissau*	1991	347.5	..	62	Nigeria*	1993	425.3	..
17	India	1983	591.6	427.9	63	Nigeria*	1996	414.5	..
18	India	1986	622.4	466.1	64	Pakistan	1987	942.5	456.1
19	India	1987	617.7	456.8	65	Pakistan	1990	989.7	462.9
20	India	1988	674.2	464.4	66	Pakistan	1993	1053.0	572.9
21	India	1989	679.3	454.1	67	Pakistan	1996	1167.4	558.0
22	India	1990	681.5	462.7	68	Pakistan*	1969	748.1	..
23	India	1992	744.7	461.7	69	Pakistan*	1979	865.1	..
24	India	1995	781.2	473.7	70	Philippines	1985	1110.2	833.1
25	India	1996	819.7	491.6	71	Philippines	1988	1205.3	919.9
26	India	1997	837.0	500.1	72	Philippines	1991	1190.0	975.0
27	India*	1965	440.8	..	73	Philippines	1994	1260.5	990.0
28	India*	1970	504.6	..	74	Philippines	1997	1342.3	1224.3
29	Indonesia	1984	965.4	559.4	75	Rwanda	1984	592.1	518.1
30	Indonesia	1987	970.7	618.6	76	Senegal	1991	851.2	707.8
31	Indonesia	1990	1085.2	689.2	77	Senegal	1994	801.7	754.1
32	Indonesia	1993	1243.6	761.6	78	Sri Lanka	1985	1472.4	875.2
33	Indonesia	1996	1561.6	962.4	79	Sri Lanka	1995	1884.1	981.4
34	Indonesia	1998	1591.3	679.9	80	Tanzania	1991	303.6	735.8
35	Indonesia*	1976	598.4	..	81	Tanzania	1993	291.3	..
36	Cote d'Ivoire	1985	1050.6	1632.1	82	Thailand	1992	2275.9	1005.1
37	Cote d'Ivoire	1986	1059.4	1485.6	83	Thailand	1998	2564.6	1543.1
38	Cote d'Ivoire	1987	1065.4	1458.1	84	Tunisia	1985	1958.2	2107.0
39	Cote d'Ivoire	1988	969.0	1159.9	85	Tunisia	1990	2065.4	2266.7
40	Cote d'Ivoire	1993	881.8	1016.9	86	Turkey	1987	2305.5	2006.6
41	Cote d'Ivoire	1995	823.1	947.7	87	Turkey	1994	2174.6	1892.7
42	Kenya	1992	640.5	996.8	88	Uganda	1989	465.8	639.7
43	Kenya	1994	546.8	819.3	89	Uganda	1992	443.1	598.4
44	Lesotho	1986	696.0	1132.6	90	Zambia	1991	348.0	434.3
45	Lesotho	1993	599.7	890.7	91	Zambia	1993	269.5	318.9
46	Madagascar	1993	528.7	..	92	Zambia	1996	279.0	345.7

Notes: 1- Data for countries with * are based on Deininger and Squire dataset. 2- Per capita consumption data are in 1985 ppp exchange rates. The World Bank consumption data has been converted from 1993 ppp to 1985 ppp base by using 1.08 factor given by the World Bank. Beyond 1992, the Penn World Tables data are extrapolated using real per capita growth of consumption in constant dollars given in WDI.

Sources: Penn World Tables, 5.6, World Bank (2001), Deininger and Squire (1996), and World Bank, WDI 2001.

Table 2: t-Tests for the household survey and the national accounts estimates average consumption

I- The ratio of survey to NA estimates (Ravallion's test):

Null hypothesis, μ (c1/c2) =	0.5	0.6	0.7	0.8	0.9	**1**	1.1	1.2	1.3	1.4	1.5
t-statistic	9.96	8.02	6.08	4.14	2.20	**0.26**	-1.68	-3.62	-5.56	-7.50	-9.44

II- The ratio of NA to survey estimates (Ravallion's test reversed):

Null hypothesis, μ (c2/c1)=	0.5	0.6	0.7	0.8	0.9	**1**	1.1	1.2	1.3	1.4	1.5
t-statistic	13.01	11.07	9.14	7.20	5.26	**3.33**	1.39	-0.55	-2.48	-4.42	-6.36

III- Tests of the difference between the average consumption means:

Null hypothesis, μ (c2-c1)=	-40	-20	**0**	20	40	80	120	140	160	180	200
(a)- t-statistic (pooled sample)	3.15	2.67	**2.19**	1.71	1.23	0.28	-0.68	-1.16	-1.64	-2.12	-2.60
(b)- t-statistic (non-independent samples)	4.08	3.46	**2.84**	2.22	1.60	0.36	-0.88	-1.50	-2.12	-2.74	-3.36
(c)- t-statistic (independent samples)	2.23	1.89	**1.55**	1.21	0.87	0.20	-0.48	-0.82	-1.16	-1.50	-1.84
(null as % of mean consumption)	*-4.6*	*-2.3*	***0.0***	*2.3*	*4.6*	*9.2*	*13.8*	*16.1*	*18.4*	*20.7*	*23.1*
(null as % of minimum consumption)	*-12.5*	*-6.3*	***0.0***	*6.3*	*12.5*	*25.1*	*37.6*	*43.9*	*50.2*	*56.4*	*62.7*

Table 3: Estimated regression of poverty (below $1 a day) on average consumption and other variables

Dependent Variable: Logistic transformation of proportion of population below $ 1 a day

	(I)			(II)			(III)			(IV)		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Constant	2.9376	0.14	21.29	3.93	0.309	12.71	3.63	0.31	11.61	3.66	0.288	12.71
C (consumption)	-0.006	0.00	-24.31	-0.00974	0.001	-8.48	-0.0084	0.00	-7.83	-0.008697	0.001	-8.70
C^2 (consumption sq.)				3.09E-06	0.000	3.19	2.47E-06	0.00	2.90	2.68E-06	0.000	3.41
REGION							-0.388	0.09	-4.29	-0.435	0.081	-5.39
D90							-0.138	0.08	-1.69			
No. of observations	58			58			58			58		
R-squared	0.934			0.946			0.967			0.965		
Adjusted R-squared	0.933			0.944			0.964			0.963		
S.E. of regression	0.342			0.315			0.250			0.256		
Mean dependent var	-0.665			-0.665			-0.664594			-0.664594		
S.D. dependent var	1.326			1.326			1.326024			1.326024		

Notes: D90 is dummy variable for the 1990 decade. REGION is an Africa(0)/Asia(1) dummy variable.
Consumption (C.) is per capita private consumption expenditure in 1985 PPP dollars.
Standard errors are White Heteroskedasticity-Consistent Standard Errors.

Table 4: Estimated regression of poverty (below $2 a day) on average consumption and other variables

Dependent Variable: Logistic transformation of proportion of population below $ 2 a day

	(I)			(II)			(III)			(IV)		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Constant	2.73621	0.13	20.27	4.07	0.15	27.31	4.05	0.15	26.31	4.05	0.15	26.42
C (consumption)	-0.0025	0.00	-15.18	-0.00537	0.00	-16.68	-0.005288	0.00	-15.63	-0.005285	0.00	-15.77
C^2 (consumption sq.)				1.17E-06	0.00	8.07	1.15E-06	0.00	7.72	1.15E-06	0.00	7.79
REGION							-0.062	0.05	-1.17	-0.060	0.05	-1.16
D90							0.010	0.05	0.19			
No. of observations	90			90			90			90		
R-squared	0.878			0.962			0.962			0.962		
Adjusted R-squared	0.877			0.961			0.960			0.961		
S.E. of regression	0.466			0.262			0.264			0.263		
Mean dependent var	0.533			0.533			0.533			0.533		
S.D. dependent var	1.328			1.328			1.328			1.328		

Notes: D90 is dummy variable for the 1990 decade. REGION is an Africa(0)/Asia(1) dummy variable.
Consumption (C.) is per capita private consumption expenditure in 1985 PPP dollars.
Standard errors are White Heteroskedasticity-Consistent Standard Errors.

Table 5: Expected Headcount Poverty in Least Developed Countries, 1995-99

	% population living below 1$ a day				% population living below 2$ a day			
	Estimate	95 % confidence interval			Estimate	95 % confidence interval		
ANGOLA	73.3	73.1	,	73.5	91.5	91.4	,	91.7
BENIN	17.7	17.4	,	18.0	64.4	64.2	,	64.5
BURKINA FASO	61.6	61.4	,	61.8	88.4	88.3	,	88.4
BURUNDI	70.8	70.6	,	71.0	90.9	90.8	,	91.0
CENTRAL AFR.R.	67.2	67.0	,	67.3	89.9	89.8	,	90.0
CHAD	81.7	81.3	,	82.1	93.7	93.6	,	93.8
Congo Dem Rep	90.6	89.9	,	91.2	96.0	95.9	,	96.2
DJIBOUTI	56.3	56.1	,	56.5	86.8	86.7	,	86.8
ETHIOPIA	85.4	84.9	,	85.9	94.7	94.5	,	94.8
GAMBIA	35.5	35.2	,	35.9	78.4	78.3	,	78.5
GUINEA	64.9	64.8	,	65.1	89.3	89.2	,	89.4
GUINEA-BISS	79.1	78.8	,	79.4	93.0	92.9	,	93.2
HAITI	39.2	38.9	,	39.5	80.2	80.2	,	80.3
LESOTHO	45.3	45.1	,	45.6	82.9	82.8	,	82.9
LIBERIA	46.7	46.5	,	47.0	83.4	83.4	,	83.5
MADAGASCAR	47.6	47.3	,	47.8	83.7	83.7	,	83.8
MALAWI	58.9	58.7	,	59.1	87.6	87.5	,	87.6
MALI	71.6	71.4	,	71.8	91.1	91.0	,	91.2
MAURITANIA	30.9	30.6	,	31.2	75.8	75.7	,	75.8
MOZAMBIQUE	40.1	39.8	,	40.3	80.6	80.6	,	80.7
NIGER	74.4	74.2	,	74.7	91.8	91.7	,	92.0
RWANDA	60.5	60.3	,	60.6	88.0	87.9	,	88.1
SENEGAL	15.0	14.7	,	15.3	60.7	60.5	,	60.8
SIERRA LEONE	60.5	60.3	,	60.7	88.0	87.9	,	88.1
SOMALIA	71.7	71.5	,	72.0	91.1	91.0	,	91.2
SUDAN	23.3	23.0	,	23.6	70.1	70.0	,	70.2
TANZANIA	79.2	78.9	,	79.5	93.1	92.9	,	93.2
TOGO	66.5	66.4	,	66.7	89.8	89.7	,	89.8
UGANDA	42.8	42.5	,	43.1	81.8	81.8	,	81.9
ZAMBIA	80.0	79.6	,	80.3	93.3	93.1	,	93.4
BANGLADESH	10.3	10.1	,	10.4	59.3	59.1	,	59.4
BHUTAN	24.8	24.5	,	25.1	76.4	76.2	,	76.5
LAOS	2.2	0.9	,	5.2	19.0	18.7	,	19.2
MYANMAR	52.3	51.7	,	52.9	88.1	87.9	,	88.3
NEPAL	40.0	39.5	,	40.4	84.1	83.9	,	84.3

Notes: Estimates are for average 1995-99 period.

Table 6: Estimated regression of average consumption of the poor (below $1 a day) on per capita consumption and other variables

Dependent Variable: Logistic transformation of annual average consumption of the poor (below $1 a day)

	(I)			(II)			(III)			(IV)		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Constant	-1.75	0.17	#####	-1.63	0.45	-3.64	-1.53	0.14	-10.85	-1.49	0.13	-11.42
C (consumption)	0.0070	0.00	20.55	0.0065	0.00	3.58	0.005884	0.00	20.24	0.0059	0.00	21.41
C^2 (consumption sq.)				3.54E-07	0.00	0.22						
REGION							7.79E-01	0.15	5.27	8.44E-01	0.12	6.88
D90							0.182	0.12	1.50			
No. of observations	58			58			58			58		
R-squared	0.893			0.893			0.948			0.945		
Adjusted R-squared	0.891			0.890			0.945			0.943		
S.E. of regression	0.518			0.522			0.369			0.376		
Mean dependent var	2.429			2.429			2.429			2.429		
S.D. dependent var	1.573			1.573			1.573			1.573		

Notes: D90 is dummy variable for the 1990 decade. REGION is an Africa(0)/Asia(1) dummy variable.
Consumption (C.) is per capita private consumption expenditure in 1985 PPP dollars.
Standard errors are White Heteroskedasticity-Consistent Standard Errors.

Table 7: Estimated regression of average consumption of the poor (below $2 a day) on per capita consumption and other variables

Dependent Variable: Logistic transformation of annual average consumption of the poor (below $2 a day)

	(I)			(II)			(III)			(IV)		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Constant	-0.8491	0.116	-7.315	-1.72	0.18	-9.43	-1.58	0.18	-9.03	-1.58	0.18	-8.88
C (consumption)	0.00241	0.00	15.63	0.0043	0.00	9.78	0.0037	0.00	8.43	0.0037	0.00	8.58
C^2 (consumption sq.)				-7.59E-07	0.00	-3.69	-6.16E-07	0.00	-3.00	-6.17E-07	0.00	-3.05
REGION							0.385	0.06	6.46	0.385	0.06	6.92
D90							0.004	0.08	0.05			
No. of observations	90			90			90			90		
R-squared	0.870			0.908			0.922			0.922		
Adjusted R-squared	0.869			0.905			0.919			0.920		
S.E. of regression	0.466			0.395			0.366			0.364		
Mean dependent var	1.273			1.273			1.273			1.273		
S.D. dependent var	1.285			1.285			1.285			1.285		

Notes: D90 is dummy variable for the 1990 decade. REGION is an Africa(0)/Asia(1) dummy variable.
Consumption (C.) is per capita private consumption expenditure in 1985 PPP dollars.
Standard errors are White Heteroskedasticity-Consistent Standard Errors.

Table 8: Expected average daily consumption of the poor in LDCs, 1995-99

(dollar per day, 1985 ppp)

	$1 Poverty Line				$2 Poverty Line			
	Estimate	95 % confidence interval			Estimate	95 % confidence interval		
ANGOLA	0.63	0.63	,	0.64	0.81	0.80	,	0.81
BENIN	0.96	0.96	,	0.96	1.45	1.45	,	1.45
BURKINA FASO	0.73	0.73	,	0.73	0.94	0.94	,	0.94
BURUNDI	0.66	0.66	,	0.66	0.84	0.83	,	0.84
CENTRAL AFR.R.	0.69	0.68	,	0.69	0.88	0.88	,	0.88
CHAD	0.55	0.54	,	0.55	0.70	0.69	,	0.71
Congo Dem Rep	0.42	0.41	,	0.44	0.55	0.54	,	0.56
DJIBOUTI	0.76	0.76	,	0.77	0.99	0.99	,	0.99
ETHIOPIA	0.50	0.50	,	0.51	0.64	0.63	,	0.65
GAMBIA	0.88	0.88	,	0.88	1.21	1.21	,	1.21
GUINEA	0.70	0.70	,	0.71	0.90	0.90	,	0.91
GUINEA-BISS	0.58	0.57	,	0.58	0.74	0.73	,	0.74
HAITI	0.86	0.86	,	0.86	1.17	1.17	,	1.17
LESOTHO	0.83	0.83	,	0.83	1.11	1.10	,	1.11
LIBERIA	0.82	0.82	,	0.82	1.09	1.09	,	1.09
MADAGASCAR	0.82	0.81	,	0.82	1.08	1.08	,	1.08
MALAWI	0.75	0.74	,	0.75	0.97	0.96	,	0.97
MALI	0.65	0.65	,	0.65	0.83	0.82	,	0.83
MAURITANIA	0.90	0.90	,	0.91	1.27	1.26	,	1.27
MOZAMBIQUE	0.86	0.86	,	0.86	1.16	1.16	,	1.16
NIGER	0.62	0.62	,	0.63	0.80	0.79	,	0.80
RWANDA	0.74	0.73	,	0.74	0.95	0.95	,	0.95
SENEGAL	0.97	0.97	,	0.97	1.50	1.49	,	1.50
SIERRA LEONE	0.74	0.73	,	0.74	0.95	0.95	,	0.95
SOMALIA	0.65	0.65	,	0.65	0.83	0.82	,	0.83
SUDAN	0.94	0.93	,	0.94	1.36	1.36	,	1.37
TANZANIA	0.58	0.57	,	0.58	0.74	0.73	,	0.74
TOGO	0.69	0.69	,	0.69	0.89	0.88	,	0.89
UGANDA	0.84	0.84	,	0.85	1.13	1.13	,	1.13
ZAMBIA	0.57	0.56	,	0.57	0.72	0.72	,	0.73
BANGLADESH	0.99	0.99	,	0.99	1.63	1.63	,	1.63
BHUTAN	0.95	0.95	,	0.95	1.40	1.40	,	1.41
LAOS	1.00	1.00	,	1.00	1.91	1.91	,	1.92
MYANMAR	0.86	0.85	,	0.86	1.12	1.11	,	1.12
NEPAL	0.90	0.90	,	0.91	1.24	1.24	,	1.24

Notes: Estimates are for average 1995-99 period.

Table 9: Validation of estimated poverty measures

	Headcount Measure of Poverty		Average consumption of the poor	
	below $1	below $2	below $1	below $2
Actual (mean)	39.4	57.1	309.9	526.3
Estimated (mean)	40.0	59.9	310.2	529.3
Mean absolute error	3.0	3.5	10.0	16.9
(% of mean poverty)	(7.5)	(6.2)	(3.2)	(3.2)
Mean absolute error of World Bank estimates	19.1	17.6	39.5	123.1
(% of mean poverty)	(48.5)	(30.9)	(12.7)	(23.4)

Notes: Mean absolute errors of World Bank estimates are measured in relation to the new actual estimates:

Table 10 : Validation of the New Poverty Estimates against the World Bank Estimates

Dependent Variable: % Population Undernourished

	(1) Combined Regression			(2) New Estimates			(3) World Bank Estimates		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Model I: Headcount Poverty (below $1 a day)									
Constant	21.24	4.11	5.17	22.14	2.66	8.33	23.33	4.33	5.39
P1 (New Estimates)	0.20	0.07	2.94	0.20	0.06	3.43			
P1 (World Bank Estimates)	0.03	0.10	0.29				0.16	0.10	1.61
No. of observations	55			55			55		
R-squared	0.183			0.181			0.047		
Adjusted R-squared	0.151			0.166			0.029		
Log likelihood	-205.94			-205.98			-210.16		
White Heter. Test:	F(5, 49) 1.442			F(2, 52) 0.363			F(2, 52) 1.426		
Model II: Headcount Poverty (below $2 a day)									
Constant	4.57	3.56	1.28	8.81	2.95	2.98	7.24	3.73	1.94
P2 (New Estimates)	0.21	0.06	3.56	0.28	0.05	6.12			
P2 (World Bank Estimates)	0.13	0.06	2.04				0.27	0.05	5.14
No. of observations	80			80			80		
R-squared	0.359			0.324			0.253		
Adjusted R-squared	0.342			0.315			0.244		
Log likelihood	-297.07			-299.16			-303.15		
White Heter. Test:	F(5, 74) 1.049			F(2, 77) 0.268			F(2, 77) 1.679		

Notes: P1 refers to headcount measure of poverty (below $1 a day). P2 refers to headcount measure of poverty (below $2 a day).

Table 11: Validation of the New Poverty Estimates against the World Bank Estimates

Dependent Variable: Human Development Indicator Index

	(1) Combined Regression			(2) New Estimates			(3) World Bank Estimates		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Model I: Headcount Poverty (below $1 a day)									
Constant	0.470	0.030	15.75	0.490	0.019	25.45	0.451	0.032	13.908
P1 (New Estimates)	-0.002	0.0005	-3.58	-0.001	0.0004	-3.55			
P1 (World Bank Estimates)	0.001	0.001	0.87				-0.0004	0.001	-0.608
No. of observations	56			56			56		
R-squared	0.200			0.189			0.007		
Adjusted R-squared	0.170			0.174			-0.012		
Log likelihood	65.43			65.04			59.37		
White Heter. Test:	F(5, 50) 2.745			F(2, 53) 1.473			F(2, 53) 6.864		
Model II: Headcount Poverty (below $2 a day)									
Constant	0.712	0.028	25.15	0.699	0.023	30.05	0.68	0.03	19.92
P2 (New Estimates)	-0.003	0.000	-6.45	-0.003	0.000	-9.28			
P2 (World Bank Estimates)	0.000	0.001	-0.81				-0.003	#####	-5.48
No. of observations	84			84			84		
R-squared	0.516			0.512			0.268		
Adjusted R-squared	0.504			0.506			0.259		
Log likelihood	84.92			84.58			67.50		
White Heter. Test:	F(5, 78) 3.71			F(2, 81) 3.032			F(2, 81) 11.177		

Notes: P1 refers to headcount measure of poverty (below $1 a day). P2 refers to headcount measure of poverty (below $2 a day).

Table 12: Validation of the New Expected Poverty Measures against the World Bank Estimates

Dependent Variable: % Population Undernourished

	(1) Combined Regression			(2) New Expected Measures			(3) World Bank Estimates		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Model I: Headcount Poverty (below $1 a day)									
Constant	21.08	4.03	5.23	21.97	2.54	8.65	23.33	4.33	5.39
P1 (Expected Measures)	0.21	0.06	3.28	0.21	0.06	3.69			
P1 (World Bank Estimates)	0.02	0.10	0.21				0.16	0.10	1.61
No. of observations	55			55			55		
R-squared	0.211			0.202			0.047		
Adjusted R-squared	0.180			0.187			0.029		
Log likelihood	-204.98			-208.52			-210.16		
White Heter. Test:	F(5, 49) 2.10			F(2, 52) 0.441			F(2, 52) 1.426		
Model II: Headcount Poverty (below $2 a day)									
Constant	1.92	3.58	0.54	6.12	3.01	2.03	7.24	3.73	1.94
P2 (Expected Measures)	0.22	0.06	3.68	0.32	0.05	6.95			
P2 (World Bank Estimates)	0.15	0.07	2.24				0.27	0.05	5.14
No. of observations	77			77			77		
R-squared	0.410			0.385			0.253		
Adjusted R-squared	0.394			0.377			0.244		
Log likelihood	-282.81			-292.71			-303.15		
White Heter. Test:	F(5, 71) 3.41			F(2, 74) 0.363			F(2, 74) 1.679		

Notes: P1 refers to headcount measure of poverty (below $1 a day). P2 refers to headcount measure of poverty (below $2 a day).

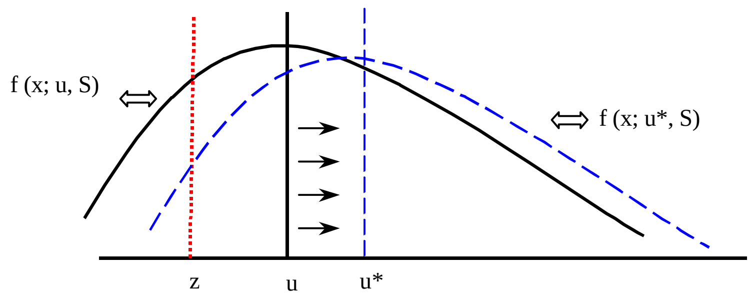
Table 13: Validation of the New Expected Poverty Measures against the World Bank Estimates

Dependent Variable: Human Development Index

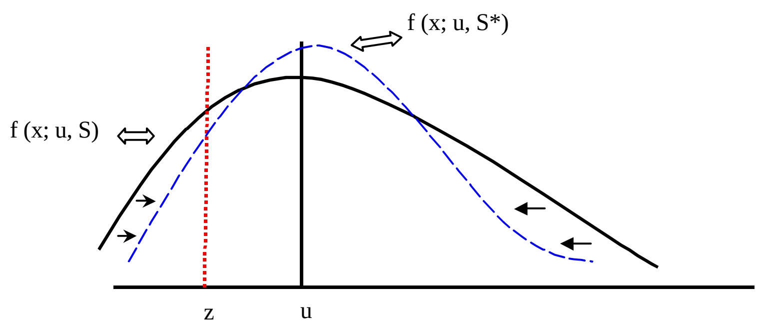
	(1) Combined Regression			(2) New Expected Measures			(3) World Bank Estimates		
Variable	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic	Coeff.	S.E.	t-Statistic
Model I: Headcount Poverty (below $1 a day)									
Constant	0.470	0.030	15.89	0.489	0.019	26.182	0.451	0.032	13.91
P1 (Expected Measures)	-0.002	0.000	-3.726	-0.001	0.000	-3.634			
P1 (World Bank Estimates)	0.001	0.001	0.898				-0.0004	0.001	-0.608
No. of observations	56			56			56		
R-squared	0.213			0.194			0.007		
Adjusted R-squared	0.183			0.179			-0.012		
Log likelihood	65.88			66.87			59.37		
White Heter. Test:	F(5, 50) 2.10			F(2, 53) 0.441			F(2, 53) 6.864		
Model II: Headcount Poverty (below $2 a day)									
Constant	0.696	0.027	26.26	0.712	0.022	32.063	0.68	0.03	19.92
P2 (Expected Measures)	-0.004	0.001	-7.961	-0.004	0.000	-10.891			
P2 (World Bank Estimates)	0.001	0.001	0.982				-0.003	0.000	-5.48
No. of observations	80			80			80		
R-squared	0.582			0.594			0.268		
Adjusted R-squared	0.571			0.589			0.259		
Log likelihood	88.76			91.91			67.50		
White Heter. Test:	F(5, 74) 3.41			F(2, 77) 0.363			F(2, 77) 11.177		

Notes: P1 refers to headcount measure of poverty (below $1 a day). P2 refers to headcount measure of poverty (below $2 a day).

Chart 1: Absolute poverty, growth, and income distribution



(a)- Poverty reduction through distribution-neutral growth



(b)- Poverty reduction through growth-neutral redistribution

Chart 2a: Headcount poverty vs per capita private consumption

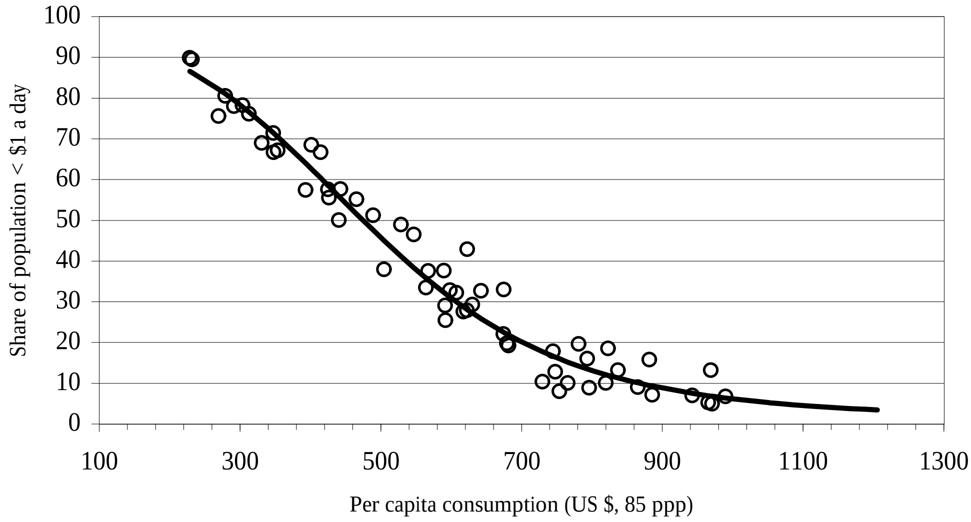
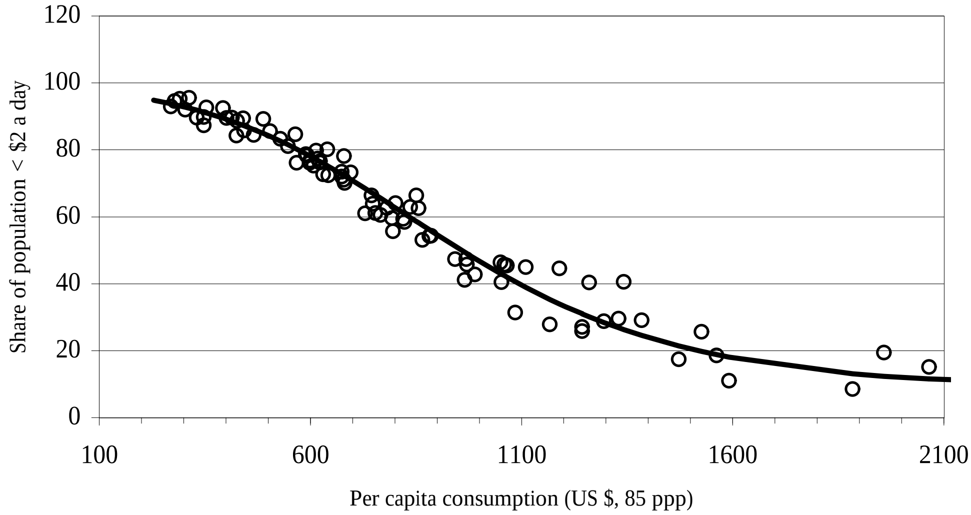


Chart 2b: Headcount poverty vs per capita private consumption



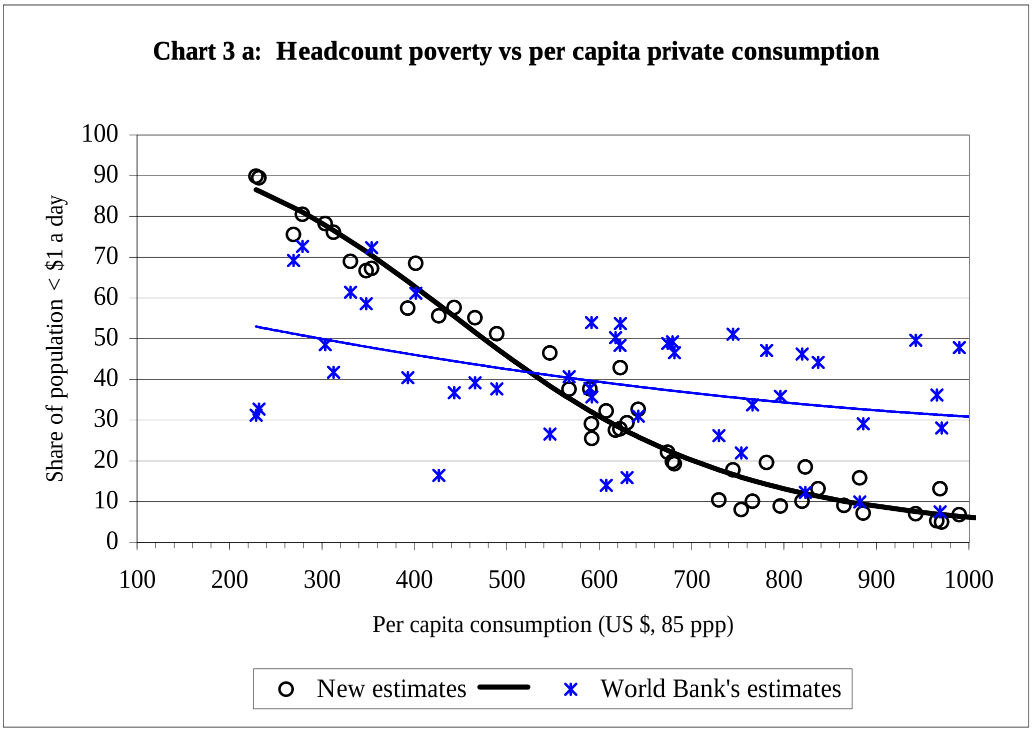


Chart 3 a: Headcount poverty vs per capita private consumption
Share of population < $1 a day
Per capita consumption (US $, 85 ppp)
New estimates
World Bank's estimates
100
90
80
70
60
50
40
30
20
10
0
100
200
300
400
500
600
700
800
900
1000

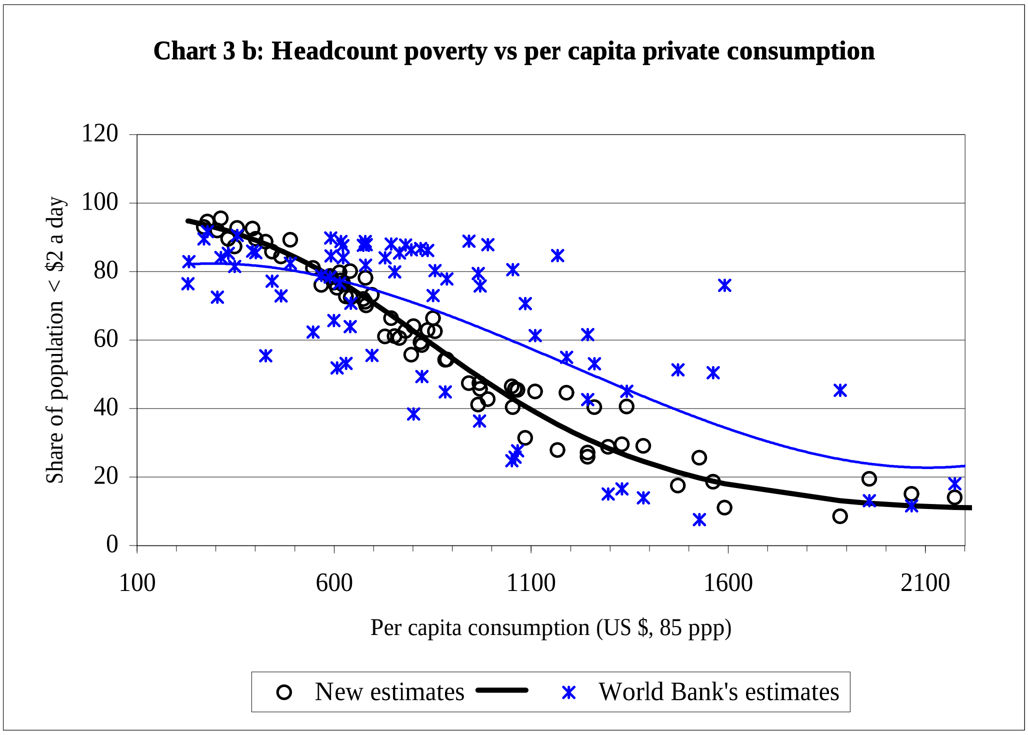


Chart 3 b: Headcount poverty vs per capita private consumption
Share of population < $2 a day
Per capita consumption (US $, 85 ppp)
New estimates
World Bank's estimates
120
100
80
60
40
20
0
100
600
1100
1600
2100

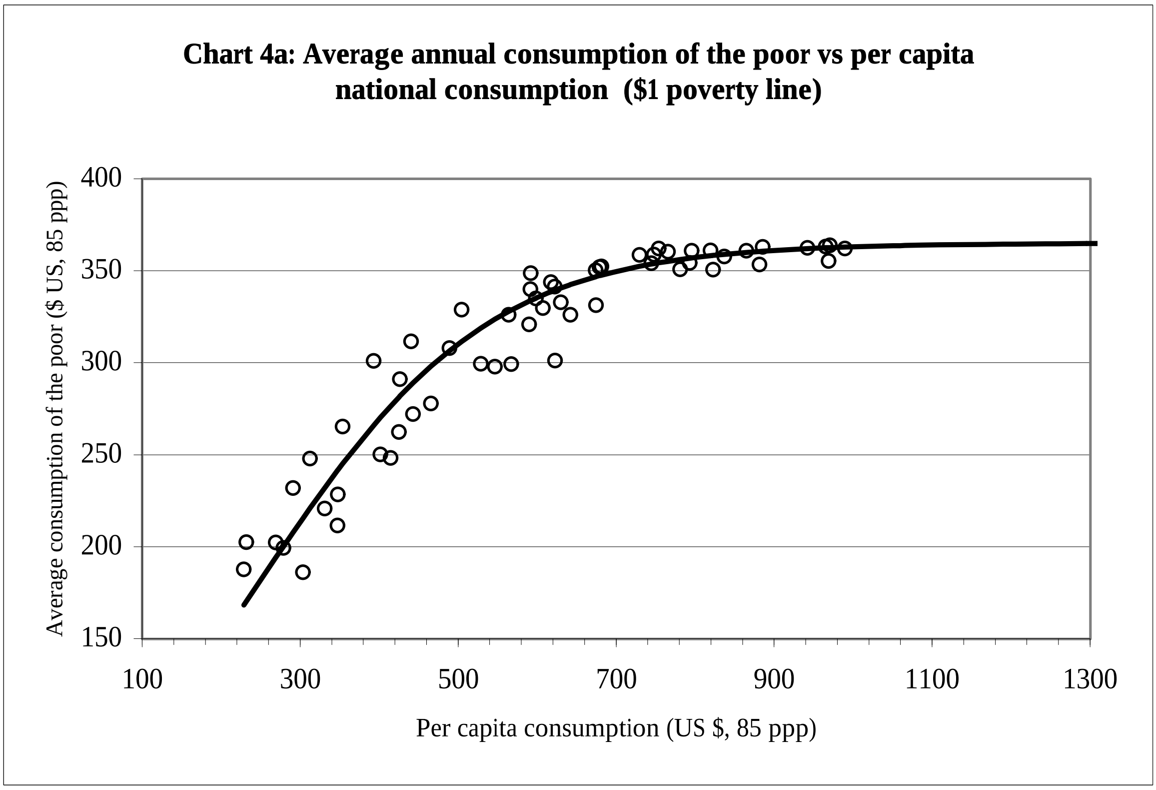


Chart 4a: Average annual consumption of the poor vs per capita national consumption ($1 poverty line)
Average consumption of the poor ($ US, 85 ppp)
400
350
300
250
200
150
100
300
500
700
900
1100
1300
Per capita consumption (US $, 85 ppp)

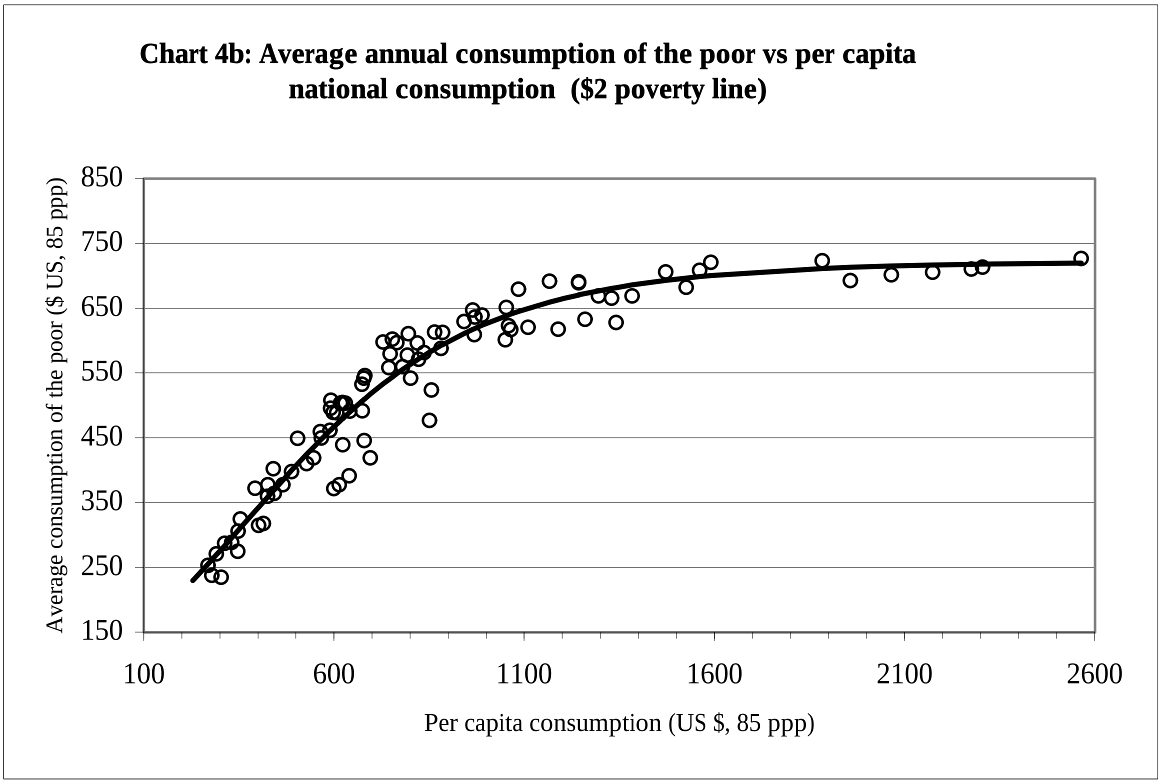


Chart 4b: Average annual consumption of the poor vs per capita national consumption ($2 poverty line)
Average consumption of the poor ($ US, 85 ppp)
850
750
650
550
450
350
250
150
100
600
1100
1600
2100
2600
Per capita consumption (US $, 85 ppp)

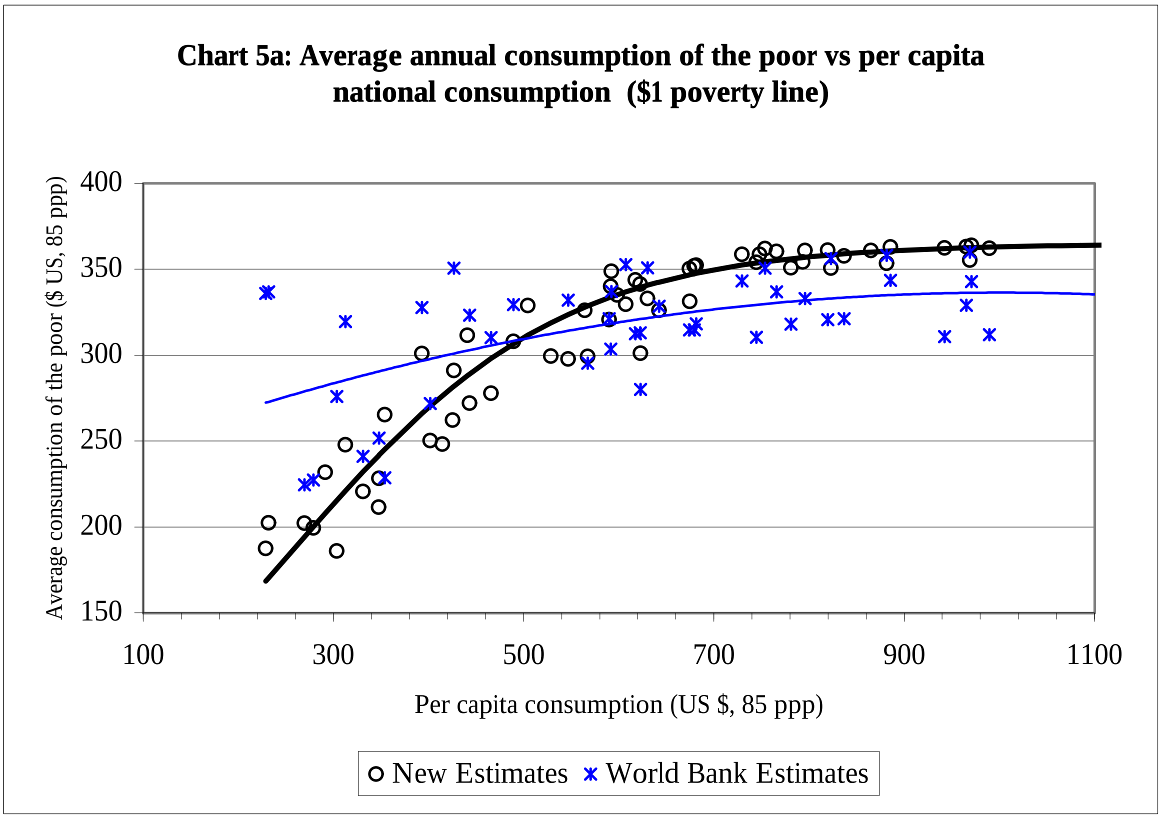


Chart 5a: Average annual consumption of the poor vs per capita national consumption ($1 poverty line)
Average consumption of the poor ($ US, 85 ppp)
400
350
300
250
200
150
100
300
500
700
900
1100
Per capita consumption (US $, 85 ppp)
New Estimates
World Bank Estimates

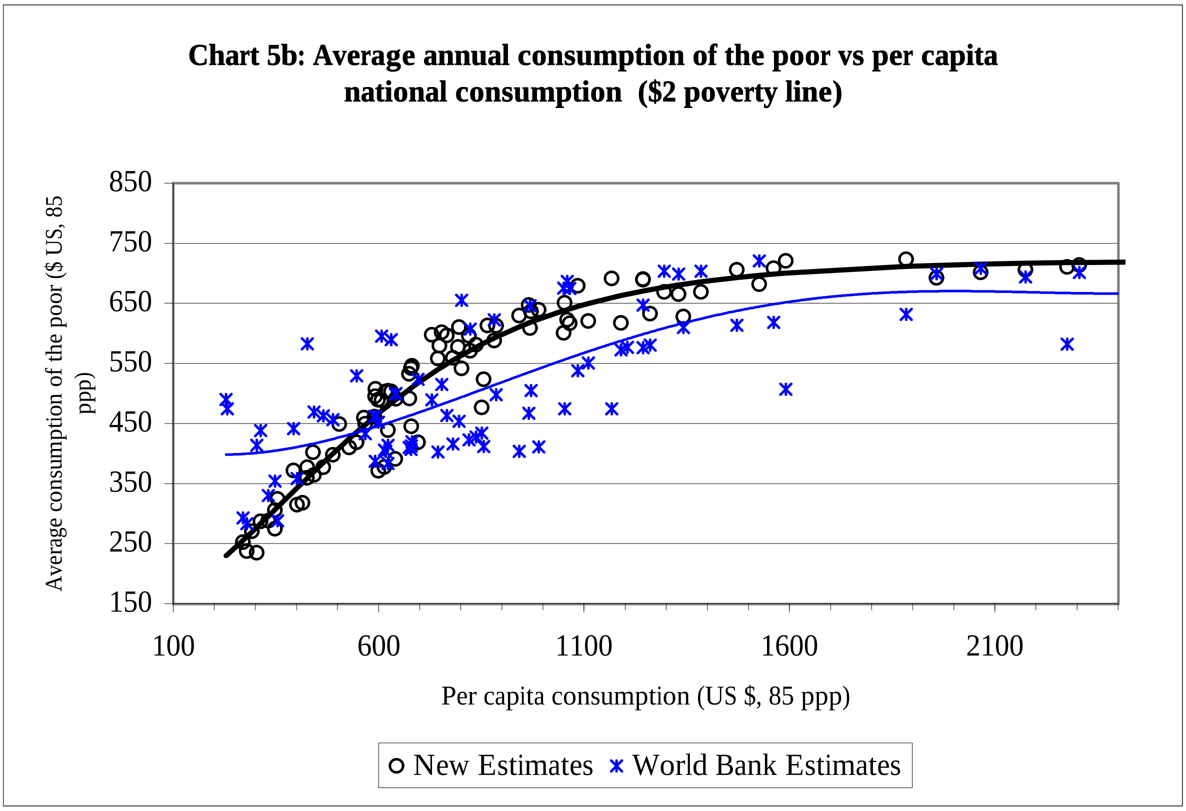
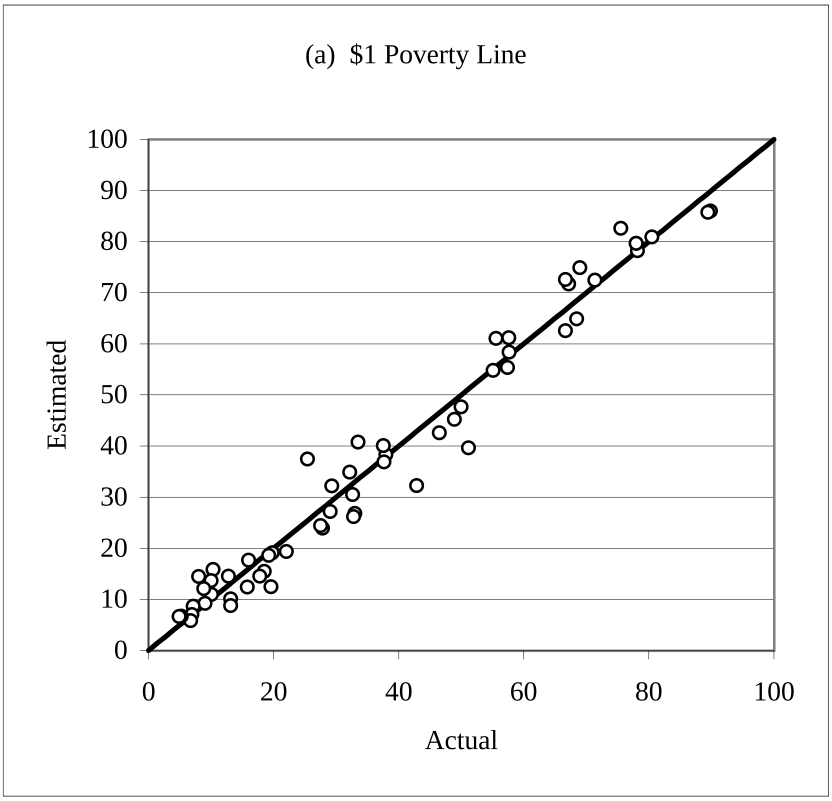


Chart 5b: Average annual consumption of the poor vs per capita national consumption ($2 poverty line)
Average consumption of the poor ($ US, 85 ppp)
850
750
650
550
450
350
250
150
100
600
1100
1600
2100
Per capita consumption (US $, 85 ppp)
New Estimates
World Bank Estimates

Chart 6: Estimated vs Actual Headcount Poverty



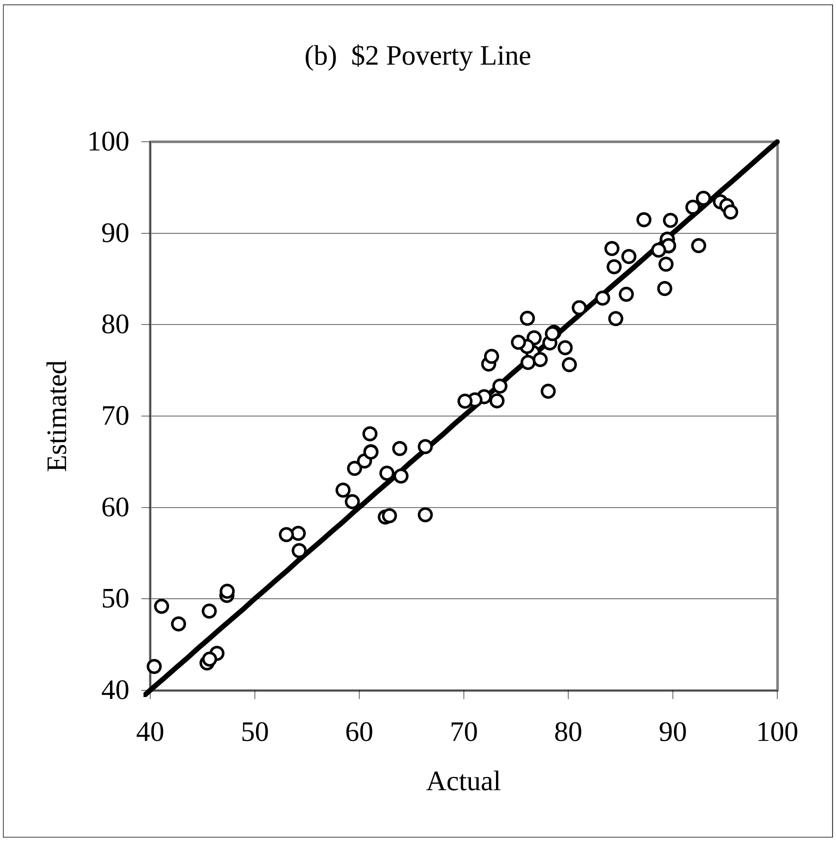
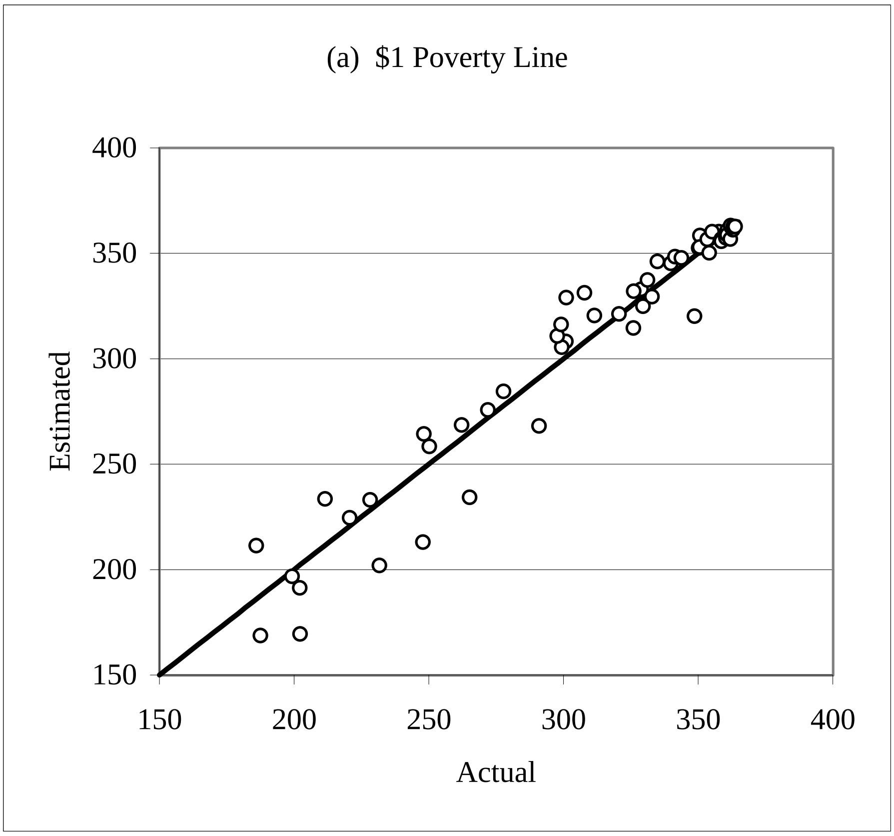


Chart 7: Average Annual Consumption of the Poor, Estimated vs Actual (in $ at 1985 ppp)



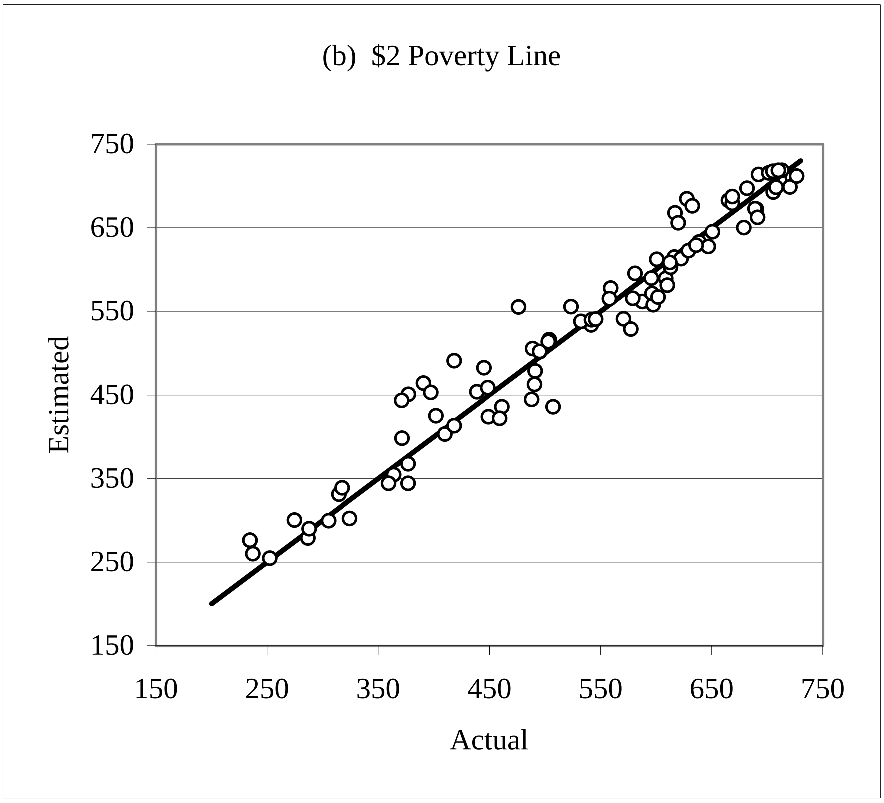


Chart 8: Generalized Poverty and Normal Poverty

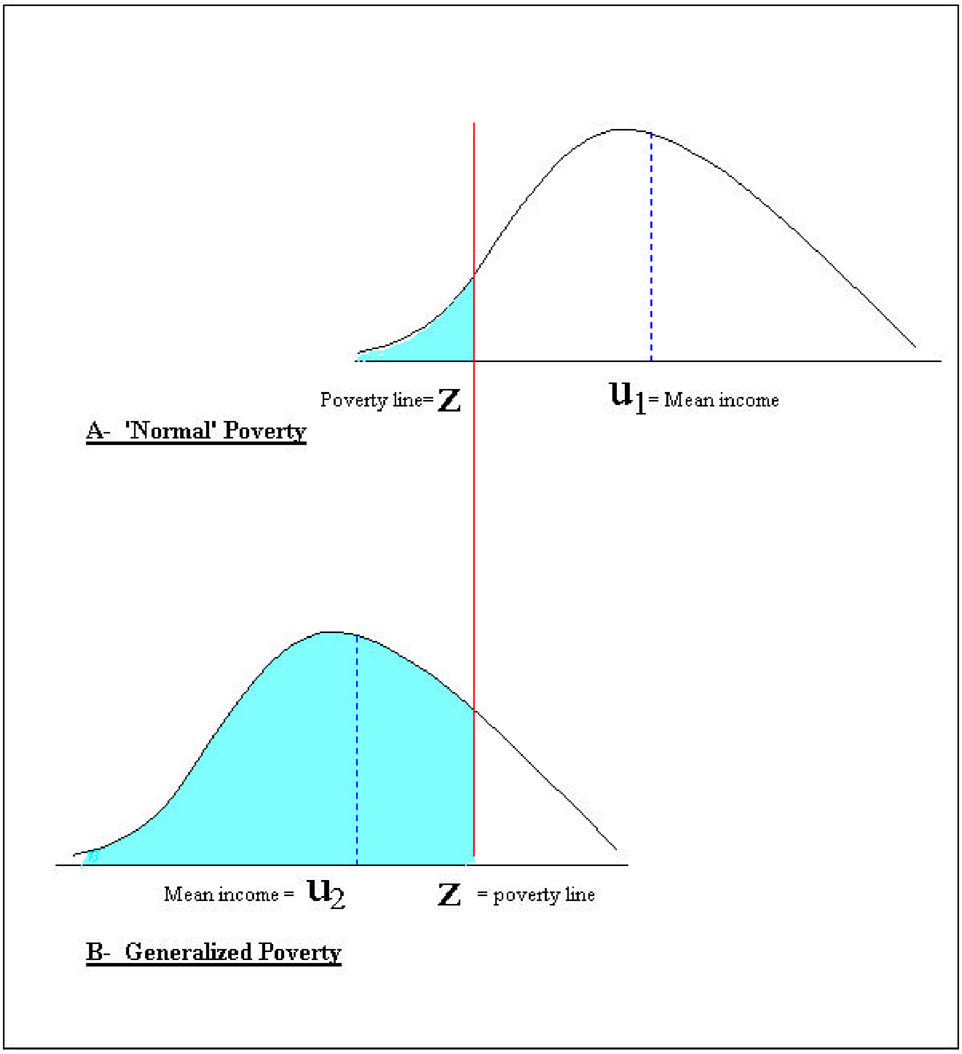


Chart 9: Headcount poverty vs per capita private consumption

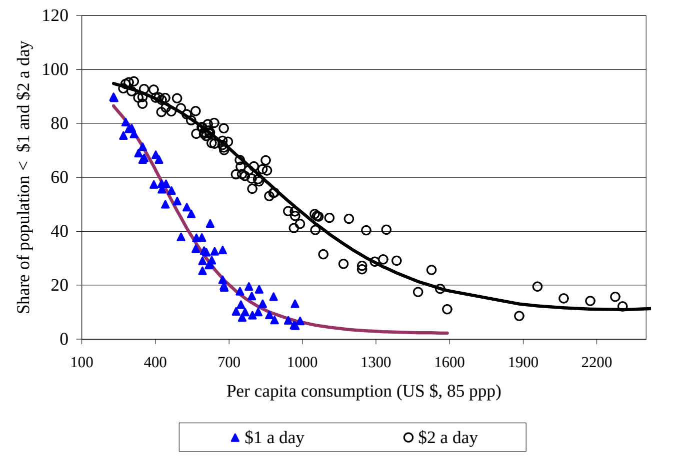
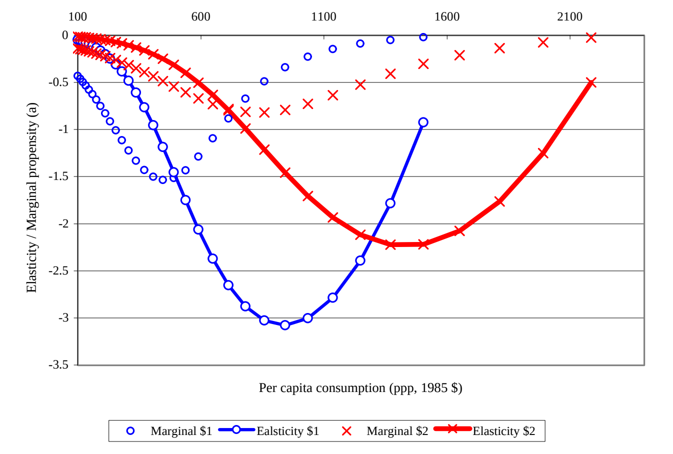
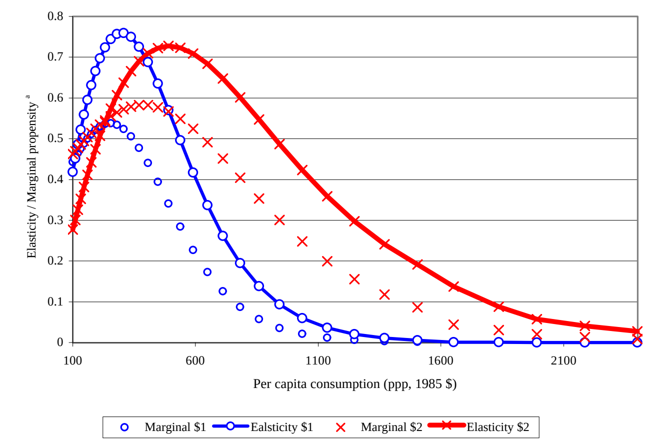


Chart 10, Poverty reduction elasticities and marginal propensities for Headcount poverty ($1 and $2 poverty lines)



Notes: (a) Per cent for elasticities, and change per $10 increase in annual per capita consumption for the marginal.

Chart 11, Poverty reduction elasticities and marginal propensities (average consumption of the poor, below $1 and $2 a day)



Notes: (a) Per cent for elasticities, and change per $1 increase in annual per capita consumption for the marginal