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The Least Developed Countries Report 2008:

Growth, Poverty and Terms of Development Partnership

Background paper

Poverty Trends in Least Developed Countries

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Background Paper No. 4

1. Introduction

In this paper we present new national accounts consistent poverty estimates for the Least Developed Countries (LDCs). The present estimates are updates of the 2002 estimates and improve on the latter in various respects (see Karshenas 2001 and LDC Report 2002 for a discussion of the earlier estimates).

- First, the availability of a much richer dataset makes it possible to use a better methodological framework to estimate national accounts consistent poverty measures for the LCDs;
- Secondly, with the availability of the new purchasing power parity exchange rate estimates in the latest Penn World Tables (hereafter PWT6.1), the present estimates can be made more directly comparable to the World Bank's survey based estimates in 1993 base year. The earlier version of the Penn World Tables (PWT 5.6) used in the estimation of the 2002 poverty measures did not provide purchasing power parity (PPP) exchange rates for 1993. Hence in 2002 poverty estimates indirect methods were used to make the $1 a day poverty line in 1985 PPP comparable with the new poverty line introduced by the World Bank ($1.08 a day in 1993 PPP exchange rates). This problem can now be dealt with in a more satisfactory manner; and
- Thirdly, the present estimates are based on a much larger dataset than in 2002, as the results of more household surveys have been made available by the World Bank.

In the next section we start by a discussion of the data and the relationship between national accounts and survey averages.

2. The International Measures of Absolute Poverty

In this paper we are mainly concerned with money-metric measures of poverty, or what are alternatively referred to as income or consumption poverty. A number of issues arise in the estimation of internationally comparable measures of absolute poverty. These relate to the choice of an internationally comparable metric, such as income or consumption; the distribution of this metric across households or individuals within each country; and a measure of poverty line which defines an internationally comparable poverty threshold. With these in hand, various measures of poverty, such as headcount measure, poverty gap, etc. can be estimated in a straightforward manner. In this paper we will be mainly concentrating on headcount measure, but much of our results can be extended to other definitions of absolute poverty as well.

Over the years, the World Bank has developed well known methodologies to deal with the above issues (Chen and Ravallion, 2001, 2004). Living standard surveys, increasingly compiled by the World Bank itself, have furnished the income or consumption metric and its distribution across a large number of countries and over time. The conversion to internationally comparable standards was originally conducted by the World Bank using the PPP exchange rate estimates by Penn World Tables (PWT5.6). The World Bank's $1 a day international poverty line was derived as the average poverty line for a number of low income countries converted in 1985 PPP exchange rates. Thus, converting average income or consumption from the surveys into 1985 international prices, and given the distribution of income/consumption within each country, internationally comparable poverty measures were calculated by the World Bank using the $1 a day and $2 a day poverty line.

Since the PWT5.6 data on PPP exchange rates for many low income countries had been extrapolated with possibly large inaccuracies, the World Bank later developed its own estimates of consumption PPP exchange rates, based on direct price and quantity data for the year 1993. Current poverty estimates by the World Bank are based on the 1993 PPP exchange rates. In 1993 international prices the $1 a day poverty line translates into about $1.08, and correspondingly the $2 a day poverty line is about 2.17.[1] A comparison between different existing PPP exchange rates, namely PWT5.6, PWT6.1 and the World Bank 1993 consumption PPP rates, and the translation of the $1 a day poverty line in each, is made in Karshenas, 2004.

At the time of the 2002 poverty estimates we did not have access to the World Bank's 1993 PPP exchange rates. We hence based the 2002 national accounts consistent poverty estimates on the available PWT5.6 data in 1985 base year and adopted the $1 a day and $2 a day poverty lines in 1985 PPP rates. For the present study, however, having access to the World Bank's consumption PPP rates, we use the 1993 rates as conversion factors and adopt the same poverty lines as the current World Bank practice. This is not to say that the existing PPP rates are highly accurate conversion factors for international comparability of poverty levels. In fact they are not, and the least requirement for valuing the consumption basket of the poor at international prices is not satisfied by the existing PPP rates. But in order to focus

[1] At the time of writing new improved PPP exchange rates have been made available by the World Bank. However, since the existing global poverty data reported on the World Bank's poverty net site are still based on

on the question of inconsistency between national accounts and survey averages, we will try to conform in all other aspects with the existing global poverty estimates.

The data used in this study are primarily based on the latest version of the World Bank poverty net data on income distribution and purchasing power parity exchange rates, and the national accounts data is based on PWT6.1.

3. The consistency of National Accounts and Survey Means

The lack of consistency between survey means and national accounts based measures of average income or consumption has long been recognized. Various authors who have acknowledged this problem have either opted using one or the other source in their poverty measurements. For example the World Bank continues to use the survey means in conjunction with survey based decile distributions to measure poverty on grounds that the nature of error in survey means is likely to be such that it does not affect poverty measures (see below). Others, e.g., Bhalla (2002) and Salai Martin (2002) use the survey distribution data in conjunction with national accounts averages to estimate global poverty. In our 2001 estimates we used a similar method, mainly due to the lack of access to the 1993 PPP data used by the World Bank in reporting survey means in international prices. But it was pointed out at the time that a satisfactory method will be to use the information in both sources, by calibrating survey means using national accounts statistics — a method which is adopted in the present paper.

A glance at Figure 1 which shows the scatter plot of survey means against national accounts averages clearly indicates the large anomalies between the two data sources and the seriousness of the degree of discrepancy between the two poverty estimation methods. In Figure 1, the income surveys are depicted by triangles and the consumption surveys by crosses, and the solid line is the 45 degree line. As can be seen, for example, countries A and B have average per capita consumption levels of about $600 according to surveys, but average consumption in country B according to the national accounts statistics is four times higher than country A. Similarly, according to income surveys, per capita income in country C is slightly above that of country D, but per capita income in country D according to national accounts is over four times higher than country C. Such discrepancies, which also apply to

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the 1993 PPP data, for comparability with the World Bank estimates we have also used the 1993 exchange rates in this study.

the changes in per capita income or consumption over time in particular countries, introduce considerable anomalies in poverty estimates based on the above two methods.

Of course, as there are important differences in coverage and definition of the survey and national accounts means, they are not expected to be equal — in the sense of following the 45 degree line depicted in Figure 1. But whatever the systematic relationship between the two variables, we argue that a minimum set of consistency criteria need to be obeyed for the survey means to produce poverty measures which do not contradict national accounts information. Firstly, if two countries A and B have the same income distribution, but country B has a higher per capita income or consumption than country A according the national accounts, then poverty in country B should be lower than country A. Secondly, if income distribution remains constant in a country, but national accounts data show growth of per capita income and consumption over time, then poverty should be decreasing in such a country. These minimal criteria imply a positive association between survey mean and national accounts averages, which we shall utilize to calibrate the survey means to be consistent with national accounts.

The reason for the need for such calibration is the large measurement errors in survey means resulting from lack of consistency in definitions and coverage in various surveys across countries and over time. The method of calibration is similar to that discussed in Karshenas (2003, 2004), where a smooth curve is fitted to the data in Figure 1, and calibrated survey means are read off the fitted curve corresponding to the national accounts means for each country. Since the curvature of the observations from income surveys and consumption surveys were clearly different, separate curves were fitted to the two set of observations. The fitted curves are shown in Figures 2 and 3 for the consumption and income surveys respectively. In both cases the national accounts measure of per capita household consumption has been used as the calibrating variable. Since almost all the LDCs have consumption surveys we will mainly focus on the results shown in Figure 2 on mean consumption. The fitted per capita consumption figures are taken as calibrated survey means for poverty measurement.

It should be noted that the fitted survey means in Figure 2 obey the minimum consistency requirements discussed above. The shape of the fitted curve in Figure 2 also highlights other important information regarding the relationship between the national accounts and survey averages. As pointed out by Deaton 2002, the definitional differences between the national accounts and survey consumption concepts imply that the national accounts per capita household consumption is likely to grow faster than average consumption from the surveys, particularly in the early stages of development. This is clearly indicated in the shape of the fitted curve in Figure 2. A comparison between the fitted curve and the 45 degree line also highlights the problem with using national accounts averages for poverty estimation. Such a practice, as in Salai Martin 2002 and Bhalla 2000, clearly leads to an overestimation of poverty reduction rates, particularly in the case of low income countries. The same applies to the poverty estimates in LDC report 2002, where the rate of poverty reduction along the growth path for some countries may have been overestimated.

4. Criticisms of the Calibration Approach

The approach adopted in this paper is not free from criticism, and has its own shortcomings – though we argue not as serious as the other approaches. The use of survey means in poverty measurement by the World Bank has been based on the contention that survey mean error is mainly due to non compliance of the rich. In that case, even though the survey mean may be biased the surveys nevertheless generate correct poverty estimates. Under these circumstances, as argued by Ravallion, 2003 and Deaton, 2003, the correction of the survey mean bias can lead to underestimation of poverty by unduly increasing the income of the poor. This is a valid argument, to the extent that it can be shown that the apparent error in survey means are in fact dominated by non-compliance error.

One indication of the problems associated with the non-compliance hypothesis is that it assumes survey means to be systematically underestimated. However, as is shown in Figure 1, in many instances, particularly in the case of low income countries which are of interest to us, surveys means are well above national accounts means. More rigorous tests also indicate that survey mean errors cannot be solely due to non-compliance. For example, as shown in Karshenas (2004), if the non-compliance hypothesis is correct, one should observe a positive relationship between survey mean error (underestimation) and poverty as measured by non-calibrated survey means, across the sample countries. This result is based on the fact that under the non-compliance hypothesis, poverty as measured by survey results will be accurate, even though the mean and distribution of the surveys are wrong. To test this hypothesis, we followed Deaton 2003 by depicting survey error as the log ratio of the survey mean over national accounts mean, and regressed this variable on the World Bank measures of $1 a day and $2 a day poverty estimates. We repeated these regressions for samples including and excluding countries where survey means were larger than national accounts averages. In none of the regressions this relationship turned out to be significant. We also added distributional variables such as the gini coefficient to the regressions but both the distribution and poverty variables turned out to be insignificant.

These results, which are similar to others found in the literature (See, e.g., Deaton 2003 and Karshenas 2004), are also highlighted by the scatter plots in Figures 4 and 5 which show the relationship between log difference in the two means and the $1 a day and $2 a day poverty lines respectively. As can be seen, the relationship between the two variables is not significant, and if anything they show a negative relationship — contrary to what the non-compliance hypothesis implies.

The above results do not of course mean that non-compliance of the rich is not a source of error in survey means. What these tests indicate is that in our sample countries there are other more important sources of error that overshadow the non-compliance error, thus lending support to our treatment of errors as more akin to random numbers rather than systematic underestimates as maintained by the non-compliance hypothesis. One may therefore argue that the lack of a significant relationship between poverty and the mean deviations between the surveys and the national accounts data, supports the practice of using the calibrated survey means combined with the distribution indicators from the surveys in poverty measurement followed here. This, however, can be criticized as it assumes the survey means to be error ridden but no adjustments are made to the distribution data from the surveys. As pointed out by Ravallion 2003, how can one assume that the shape of the distribution is correct but its mean is error ridden?

It is likely that both the survey mean and its distribution are subject to large measurement errors. The question is how significant these errors are and what can be done about them. Measurement errors in surveys will always exist, but the question that one needs to address is how important the errors are and how significantly they can affect poverty estimates. As to the first question, as seen in the previous section, the measurement errors in means appear to be too large to be ignored. The coefficient of variation of the log ratio of survey to national accounts mean is about 1.4 for consumption surveys, as compared to a coefficient of variation of 0.19 for the Gini coefficient for sample countries. What is more important to note, however, is that while the errors in survey means have first order effects on poverty measurements, the effect of the distribution errors is only of second order, and hence likely to be much less significant. This is shown in Karshenas 2004, where the addition of a value as large as one standard deviation to Gini coefficients in the sample countries changes poverty measures relatively much less than those arising from mean adjustment resulting from the calibration of survey means.

Given the lack of significant observable relationship between survey mean errors and distribution indices, it is not clear how best to adjust the decile data without further research. Given the relative stability of the decile distribution the best strategy may be to leave them as they are. As we shall see below, variations in mean consumption appear to have a more significant impact on poverty than distributional changes in the income ranges relevant to the LDCs. Furthermore, considering that in our sample countries on average over 70 per cent of expenditure or income belongs to the top 40 per cent of income groups, much of the adjustment in survey mean, keeping the decile distribution constant, will be allocated to the rich households.

5. **The National Accounts Consistent Poverty Estimates for the LDCs**

Using the calibrated survey means in 1993 PPP values and the decile distribution from the surveys we estimated headcount poverty for individual countries for the $1 a day and $2 a day poverty lines. It should be noted that we are using the same PPP exchange rates as the World Bank and the poverty lines are also the same ones as used by the Bank (namely, $1.08 a day and $2.17 a day). Hence the differences between the present estimates and the estimates by the World Bank are the result of the calibration of the survey means in this paper in order to make our estimates consistent with national accounts data. Since the existing surveys for the LDCs by and large cover consumption surveys, we shall only focus on the countries where consumption surveys are available. As shown in Karshenas and Pyatt 2006, income surveys have a very different distribution as compared to consumption surveys, and hence mixing the two data sets will be problematic.

Kakwani and Son 2004 have criticized the $1 a day poverty line, and have attempted to construct an international poverty line for low income countries based on the minimum required calorie intake. The poverty line they come up with is $1.22 a day in 1993 PPP values. We have also estimated poverty measures on the basis of this new poverty line using both the World Bank methodology and the calibration method used here. All poverty measurements are made by using the POVCAL programme (adopting the Beta Lorenz curve method[2]). Estimates for LDC countries for which the World Bank reports survey data are shown in Table 1. All of the LDC countries have consumption surveys with the exception of Haiti where poverty estimates are based on income survey.

[2] For a review and appraisal of the Beta and GQ Lorenz curve methods used in POVCAL, see Datt 1998 and Minoiu and Reddy, 2007.

A number of points stand out. Firstly, it should be noted that contrary to the predictions of the non-compliance hypothesis, the new poverty estimates based on calibrated survey means do not systematically underestimate poverty as compared to the World Bank estimates. In large number of countries the new estimates are higher than the World Bank estimates and in some cases such as Ethiopia and Uganda the new estimates are considerably higher. A second observation is that according to the new estimates, in the case of a large number of countries where poverty can be observed over time, the decline in poverty is much less than those estimated on the basis of the conventional method.

6. Poverty Curves and Prediction of Poverty trends in the LDCs

We finally explore the possibility of predicting poverty trends for LDC countries and years where survey data are not available. As in *LDC Report 2002*, one can base such estimation on the empirical poverty curves, provided that the fit of the poverty curves can allow such estimation with an acceptable degree of precision. As discussed in Karshenas 2001, the poverty curve depicts the relationship between absolute poverty and mean income for given poverty line, for the 'average' country over time. Given the poverty line, z, and the mean income in the 'average' country, m, poverty is uniquely determined as a function of the distance between m and z, f(m/z). In the case of headcount poverty the function f(m/z) defines the proportion of the population living below the poverty line z. As the mean and distribution of income in the 'average' country evolves over the development path, f(m/z) traces the poverty curve as a function of m/z . The shape of the poverty curve depends on the relative variations of income distribution and per capita income over the development path, but given the relatively larger variations of mean income referred to in section 5, one would expect a downward sloping curve (see Karshenas and Pyatt 2006 for a more detailed discussion).

As in Karshenas 2001, we estimate the poverty curve on the basis of the empirical observations of headcount poverty across countries and over time for the sample countries with available data. The scatter plot of the new national accounts consistent poverty estimates is shown in Figure 6, along with the fitted poverty curve. Since the survey data for most LDC countries cover per capita consumption, Figure 6 is based on observations with consumption poverty. Hereafter, any reference to income distribution thus refers to the distribution of consumption expenditure. The vertical distances between individual observations and the fitted poverty curve, indicates the divergence of income distribution in each country from the 'average' country.

As Figure 6 shows, for income ranges where headcount poverty is above 50 per cent, the dispersion of observations around the poverty curve is extremely low. We used this fact in *LDC Report 2002* to predict poverty in LDC countries where only per capita consumption data based on national accounts was available and reliable surveys did not exist (more on this below). However, for income ranges which imply headcount poverty below 50 per cent, the dispersion can be considerable, and since in our current sample there are some LDC countries where for low poverty lines, such as the $1 a day poverty line, headcount poverty can be below 50 per cent, we need to investigate alternative methods where the available information on income distribution can be used to improve precision. In general, however, the evidence shown in Figure 6 implies that poverty curve can be used to make quite precise estimates of headcount poverty for the LDC countries for the $2 a day poverty line. For this higher poverty line, headcount poverty in most LDCs is well above 50 per cent.

In order to improve the accuracy of poverty predictions by incorporating information on income distribution, we have regressed headcount poverty on polynomials of mean consumption, gini coefficient, and cross products of mean consumption and gini coefficient, in a fixed effect panel model where dummy variables capture country heterogeneity in the shape of income distribution curve not captured by the Gini coefficient. To include poverty measures based on both the $1 and $2 a day poverty lines, the mean consumption is normalized by poverty line (m/z) and the cross products are entered as (m/z)(1-gini), or the Sen index normalized by the poverty line. Table 2 reports the results with polynomial degrees that achieved the best fit. It is not surprising to find that the regression achieves almost perfect fit, with an adjusted R squared of over 99.5 per cent. The standard deviation of predictions from this regression for all the observations has a mean of

Table 2, Fixed Effects Regression of headcount poverty on mean consumption and gini coefficien

Dependent Variable h

	Coef.	Std. Err.	t
m^{-1}	-2028.934	459.3191	-4.42
m^{-2}	218.1906	52.84214	4.13
ln(m)	-3553.99	782.1864	-4.54
m	2908.492	661.9491	4.39
m2	-610.4642	156.392	-3.9
m3	94.77403	28.10431	3.37
m4	-9.257247	3.197127	-2.9
m5	0.5041332	0.2019888	2.5
m6	-0.011643	0.0053632	-2.17
m(1-g)	156.0749	84.81858	1.84
m(1-g)2	-316.8414	72.28687	-4.38
m(1-g)3	196.5908	38.14994	5.15
m(1-g)4	-58.2625	11.30632	-5.15
m(1-g)5	8.413027	1.719893	4.89
m(1-g)6	-0.474661	0.1038129	-4.57
g	-1.597147	0.7132924	-2.24
g2	0.0362569	0.0161403	2.25
g3	-0.000306	0.0001247	-2.45
Constant	-494.346	159.7777	-3.09
no. of observations			408
Adj R-saured			0.9949

Notes: m is normalized by poverty line. m2 m3, etc are higher powers of m/z. m(1-g)2 m(1-g)3 etc. are higher powers of m(1-g). g is the gini coefficient. h refers to national accounts consistent poverty estimates based on $2 a day and $1 a day poverty lines.

0.39 and variance of 0.15, and the standard deviation of forecasts has a mean of 1.99 with variance 0.03. The predictions of the regression are plotted against the actual poverty estimates in Figure 7. As can be seen, the scatter plot closely follows the 45 degree line with minimal prediction errors.

In Figure 8 we have plotted the predictions from the regression in Table 2 for observations where poverty is higher than 50 per cent, against actual poverty. Figure 8 also shows predictions from the poverty curve in Figure 6, based solely on per capita consumption information. The figure shows that the predictions from the two methods, in the case of countries with poverty above 50 per cent, are close — though the new method has noticeably lower prediction errors. This gives support to the practice followed in LDC report 2002, where the poverty curve was used to predict poverty in the case of LDC countries with very low per capita income, where survey information was not available. As can be seen from the data in Table 1, in the current sample almost all of the LDC countries show headcount poverty levels well above 50 per cent in the case of the $2 a day poverty line, both for the World Bank estimates and the national accounts consistent estimates. However, based on the $1 a day poverty line a large number of LDC countries have headcount poverty well under 50 per cent (Table 1). This makes it necessary to explore the possibilities of making more precise predictions using the available information on income distribution.

The question may arise that once we have the information on both the Gini coefficient and average income, poverty can be measured directly and hence no matter how precise the above type of indirect prediction methods may be they will be devoid of practical value. This is not however entirely correct. Even if we can make relatively accurate extrapolation of the Gini coefficient for some countries, this will not be sufficient for estimating headcount poverty, unless we make further assumptions about income distribution — e.g., log-normality assumption. However, a glance at Table 2 will be sufficient to show that the log-normal assumption is not an appropriate one. Given the nature of the income distribution data available, the indirect method also allows the examination of the sensitivity of the poverty estimates to various distributional assumptions in a practical manner. Given the nature of the available data in the case of the LDCs, this proves a valuable tool in producing time series estimates of poverty while providing us with some idea about the degree of reliability of such estimates. The LDC countries fall into four categories in terms of availability of data:

Group A countries are those countries for which numerous surveys exit and national accounts data on per capita consumption in 1993 PPP is also available.

Group B are countries where distribution information is scant, no more than one or maximum two surveys, but national accounts averages are available.

Group C are countries where no distribution data is available but national accounts averages in 1993 PPP exchange rates are available.

Group D are countries where there are no survey data available, nor do they have PPP exchange rate estimates. In this group we can also include countries for which we may have scant survey information but national accounts averages are missing.

The case of group D countries is rather straightforward. In the case of this group of countries we cannot estimate internationally comparable poverty estimates. Excluding these countries we are left with 30 LDC countries that fall into one of the other groups.

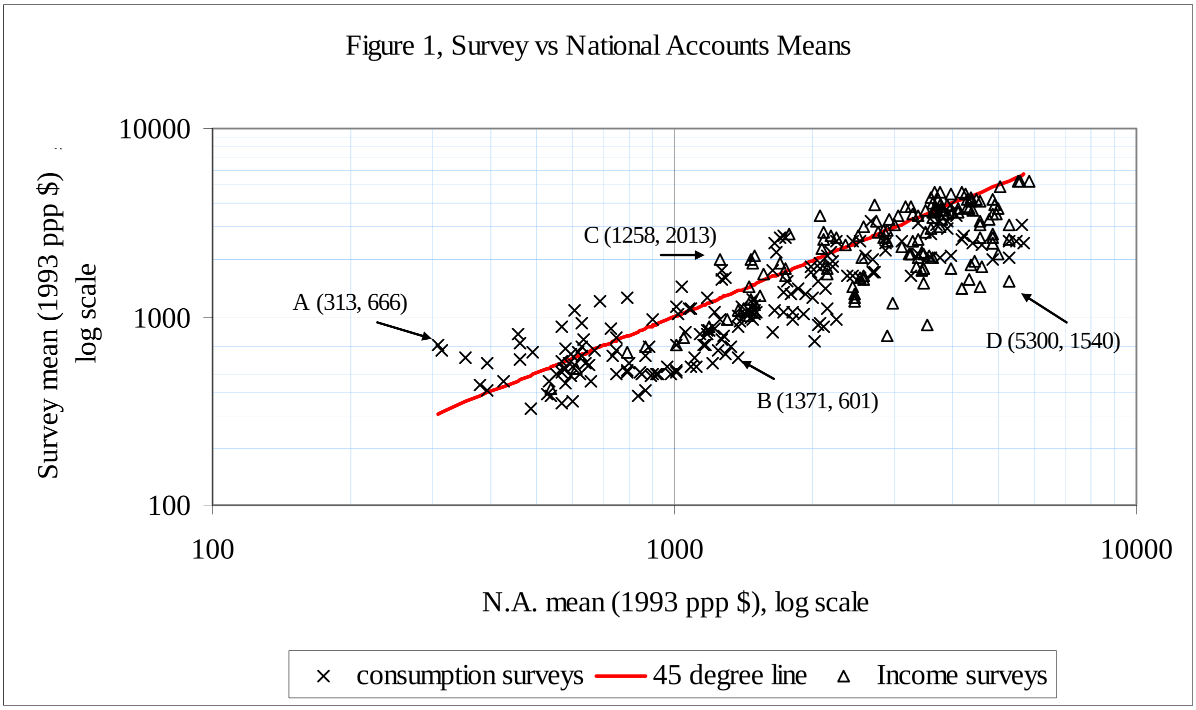
In the case of countries in group A we extrapolate the distribution of consumption, as represented by the gini coefficient, on the basis of exiting survey distribution data. For the end years, before the first survey and after the last survey, we assume income distribution remains constant. Given the relatively slow changing characteristic of income distribution, and depending on the frequency and spacing of the surveys, we should be able to come up with relatively reasonable estimates of income distribution for this group of countries. Using the gini coefficient and mean calibrated consumption for these countries, we produce time series estimates of headcount poverty on the basis of the regression equation in Table 2. As noted above the use of the regression model involves prediction errors of negligible magnitude, but it helps to investigate the sensitivity of our estimates to variations in income distribution which can be a more important source potential error. In the case of this group of countries, we examine the sensitivity of poverty estimates to distributional changes by estimating poverty trends assuming the lowest achieved and the highest achieved gini coefficients in addition to the main estimates. The cases of a few countries from this group of countries can be used to explore the nature of the sensitivity of poverty estimates to income distributional changes.

Figures 9 to 26 help explore the case of seven countries where three or more surveys are available. The case of Bangladesh as an example of Asian LDCs in the group is shown in Figures 9 and 10. Figure 9 relates to $1 a day poverty measure and Figure 10 is for $2 a day headcount poverty. Bangladesh has had six surveys between 1983 and 2005 according to the World Bank databank. The Gini coefficient started as its minimum of 25.88 in 1983 and increased to its maximum at 33.42 in last survey in 2000. Much of the increase was between 1991 and 2000 when the Gini coefficient increased from 28.2 to 33.42, by over 15 per cent. The solid line in Figures 9 and 10 show the main estimates of headcount poverty with the gini coefficient extrapolated between the surveys as discussed above. Each figure also shows the trends in headcount poverty assuming a constant Gini coefficient at its minimum and maximum levels. Our poverty estimate based on the extrapolated gini coefficients thus fall between these two bands, which indicates the maximum error that can be involved during periods where due to lack of distribution data we assume the distribution to have remained constant. This information is particularly useful where poverty estimates are made in the case of countries in other groups where only one gini coefficient is available and hence one has to assume the same distribution for the entire period.

An important fact that stands out in all the countries depicted in Figures 9 to 26 is that while distributional factors seem to have relatively important effect on $1 a day headcount poverty, the effect in the case of $2 a day is not noticeable. This conforms to what was discussed above and is explained by the fact that when poverty reaches the 70 to 90 per cent ranges, clearly changes in the shape of the distribution curve cannot bring about much change in poverty in either direction (see, Karshenas 2003). Another implication of this phenomenon is that for countries where surveys do not exist but poverty is higher than the 50 per cent range one may be able to estimate this by extrapolation based on the information about per capita consumption.

Another important type of information conveyed by Figures 9 to 26 is that one can disentangle the effect of disbtributional changes on poverty by focusing on the movement of the main poverty estimate *vis a vis* the minimum and maximum bounds. For example, with one or two exceptions, the figures indicate that poverty has increase in many LDCs since the 1990s due to worsening distribution of income. This happens when the main estimate trend shifts from the minimum curve to the maximum curve, irrespective whether poverty is increasing or falling (e.g. Bangladesh and most others). The distributional changes are poverty reducing when the reverse has happened (e.g., Burkina Faso or Ethiopia).

The poverty trends for the LDC countries (in groups A, B and C) in the form of the main estimates are in the attached spread sheet. These are based on the equation in Table 2, and are remarkably in conformity with the actual estimates in Table 1.



Source: World Bank (2007) for survey data and PWT6.1 for national accounts data.
Notes: A = Ethiopia 2000 B= Madagascar 1980, C= Guyana 1992, D= Mexico 1992

Figure 2, Survey vs National Accounts Consumption Means with fitted regression lines

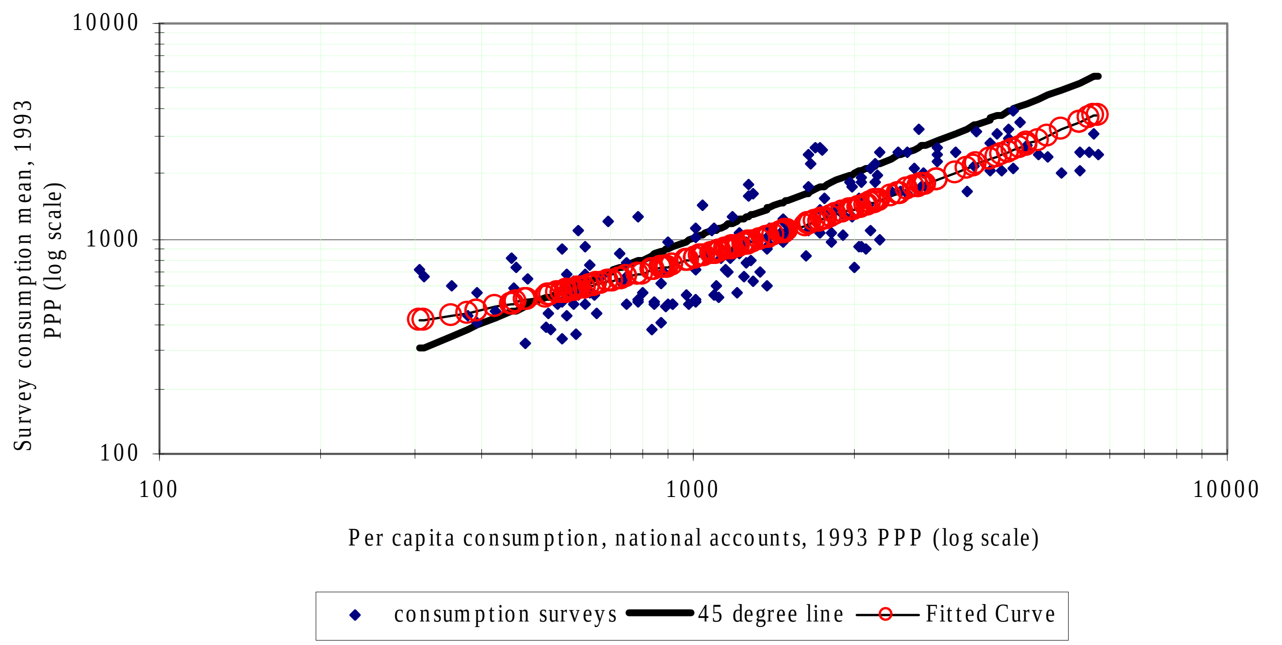


Figure 3, Survey income vs National Accounts Consumption Mean with the fitted curve

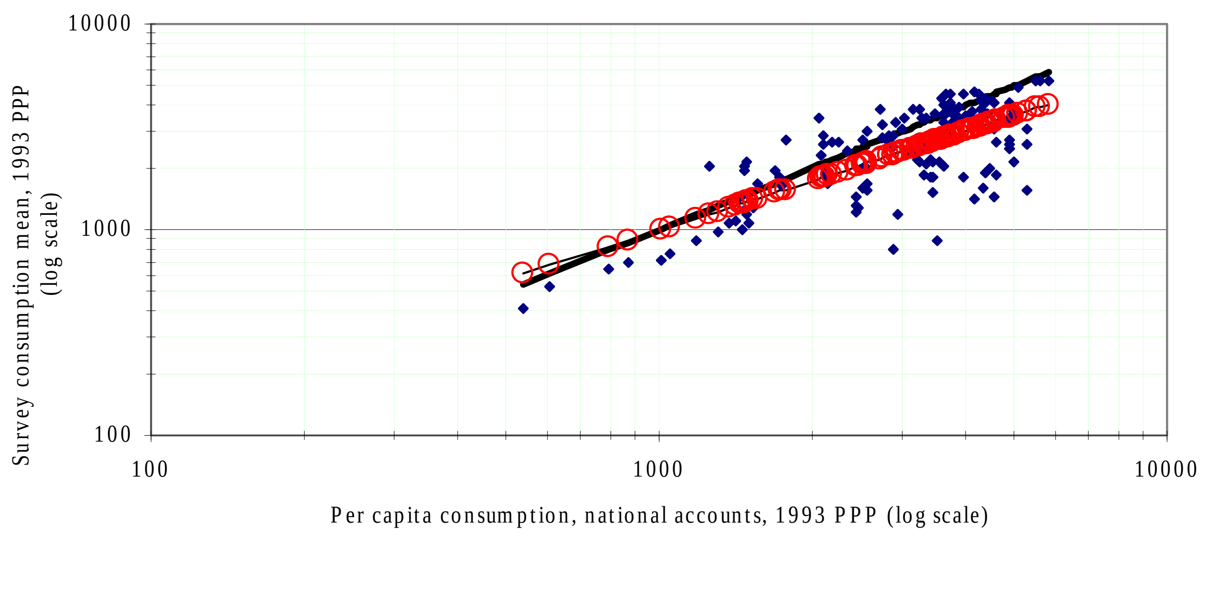


Figure 4. Log Mean Ratio against $1 a day Headcount Poverty

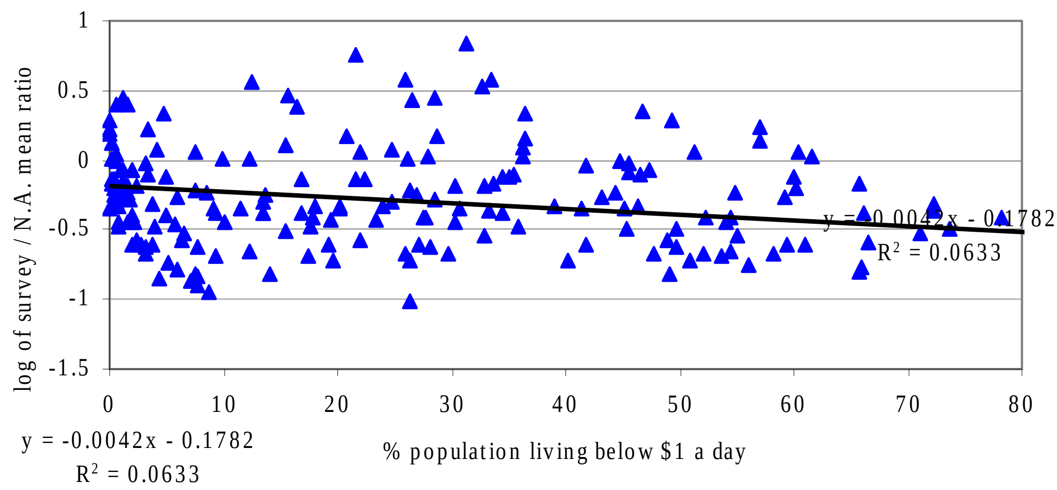
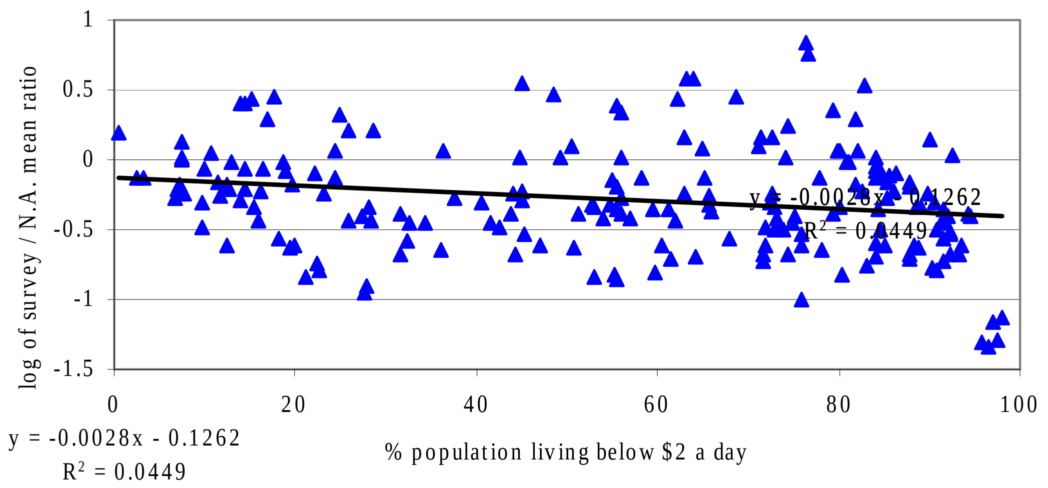


Figure 5. Log Mean Ratio against $2 a day Headcount Poverty



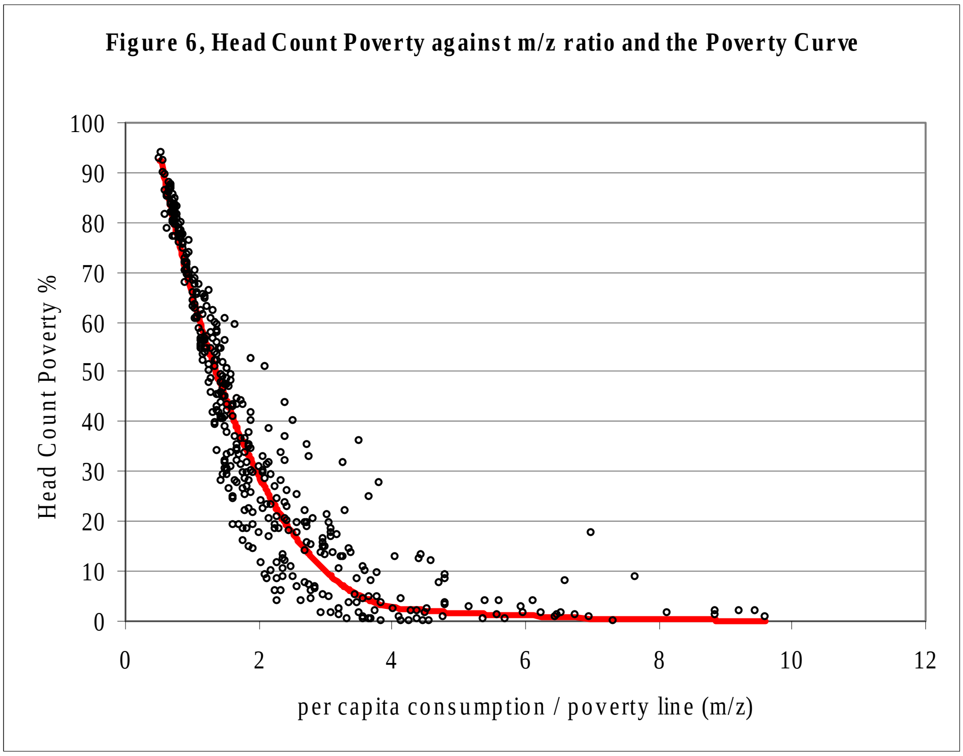


Figure 6, Head Count Poverty against m/z ratio and the Poverty Curve
100
90
80
70
60
50
40
30
20
10
0
Head Count Poverty %
0
2
4
6
8
10
12
per capita consumption / poverty line (m/z)

Figure 7, Predicted vs Actual Poverty Estimates

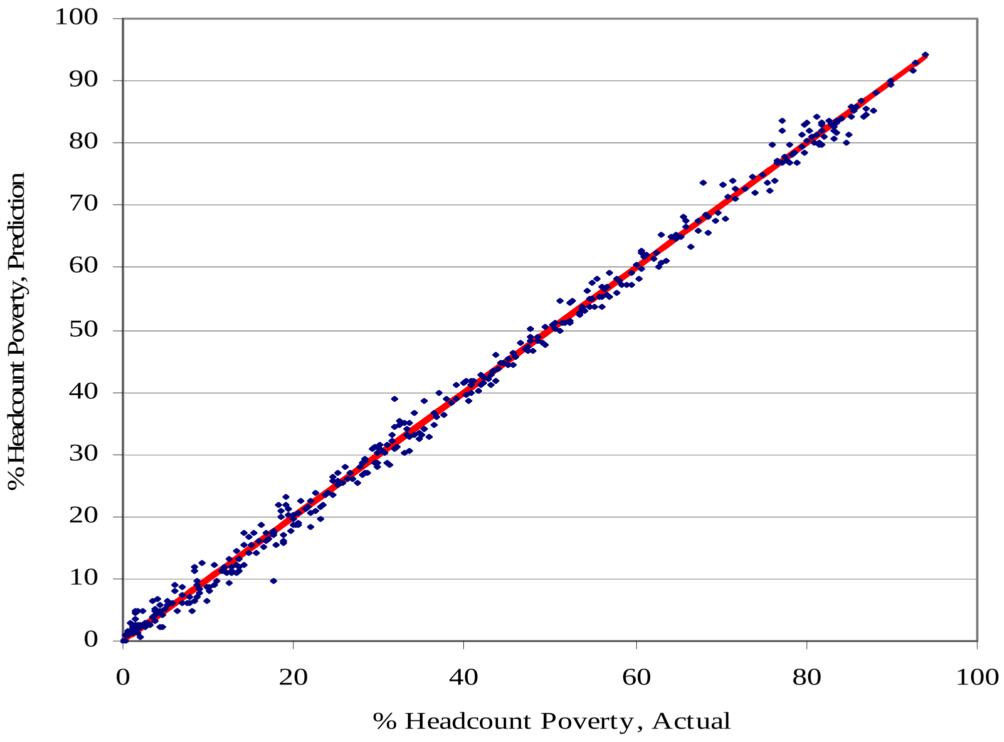


Figure 8, Predicted vs Actual Poverty Estimates, Old and New Methods (above 50% poverty sample)

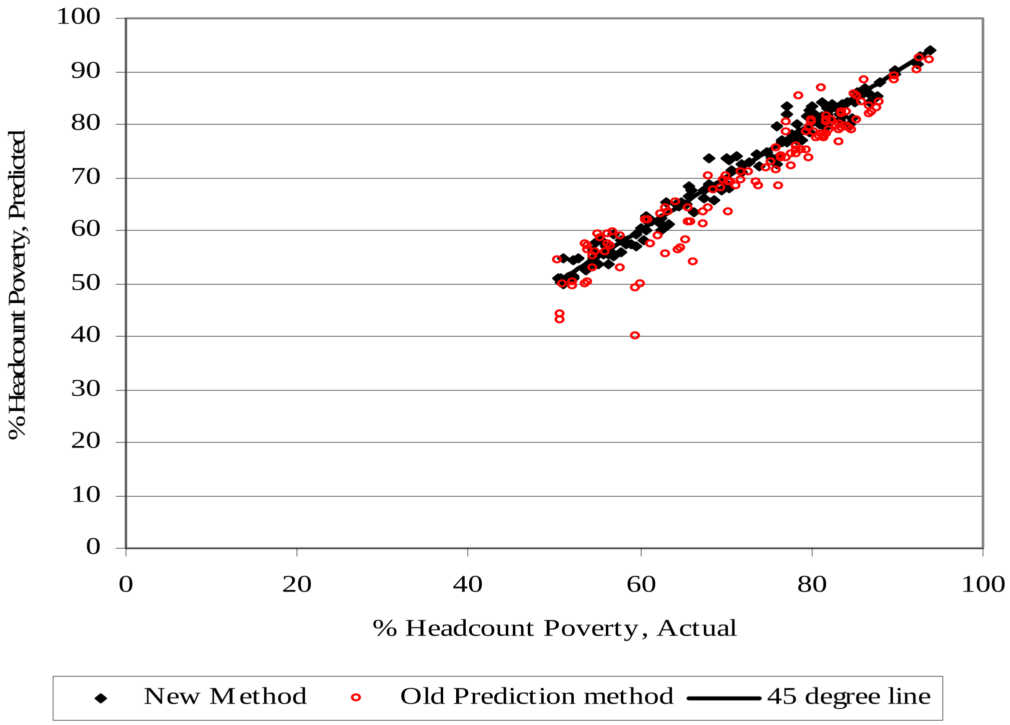


Figure 9, Headcount Poverty under different Distribution Assumptions
Bangladesh 1970-2005

($1 a day)

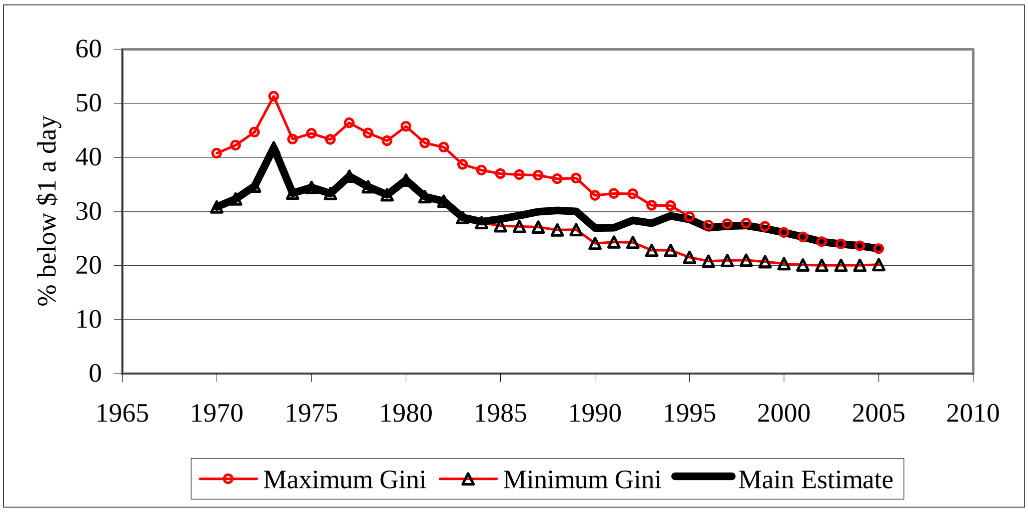


Figure 10, Headcount Poverty under different Distribution Assumptions
Bangladesh 1970-2005

($2 a day)

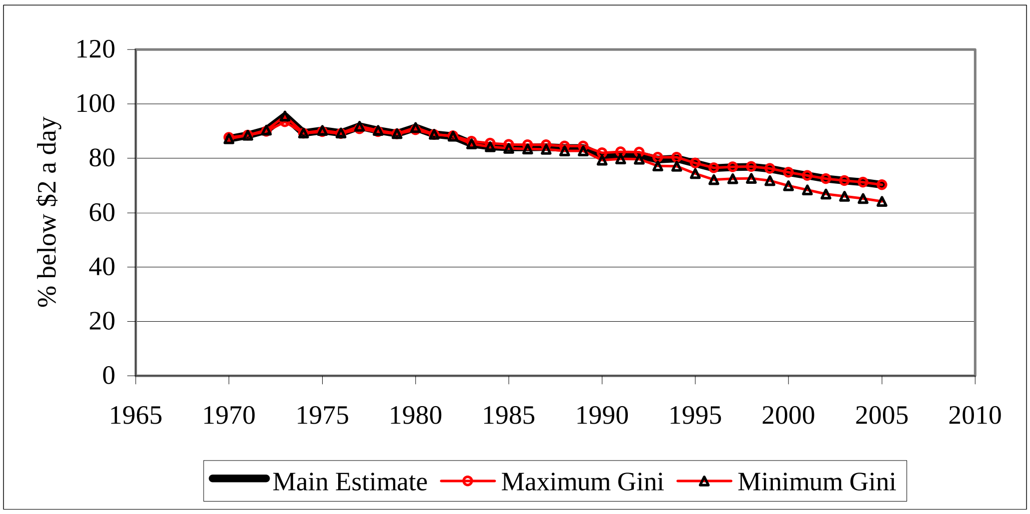


Figure 11, Headcount Poverty under different Distribution Assumptions
Burkina Fasc 1970-2005

($1 a day)

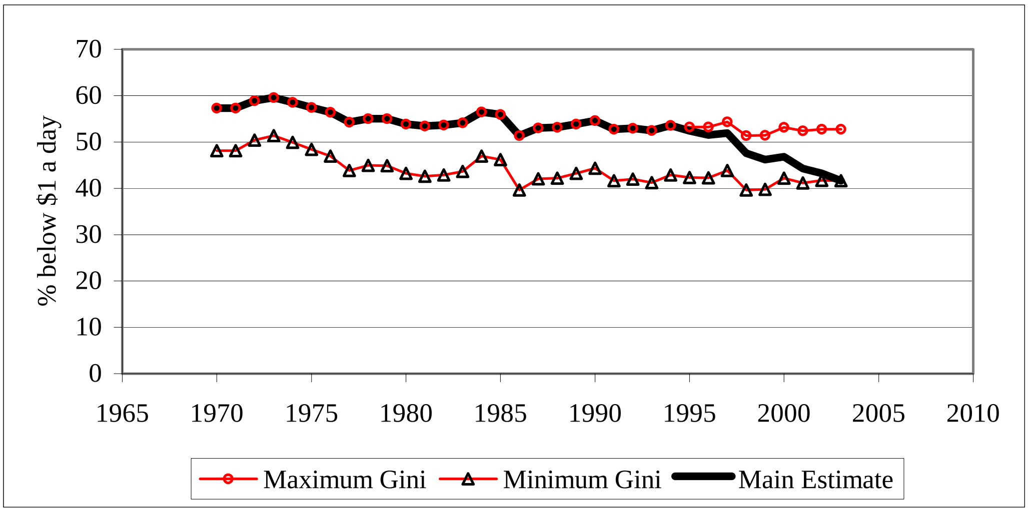


Figure 12, Headcount Poverty under different Distribution Assumptions
Burkina Fasc 1970-2005

($2 a day)

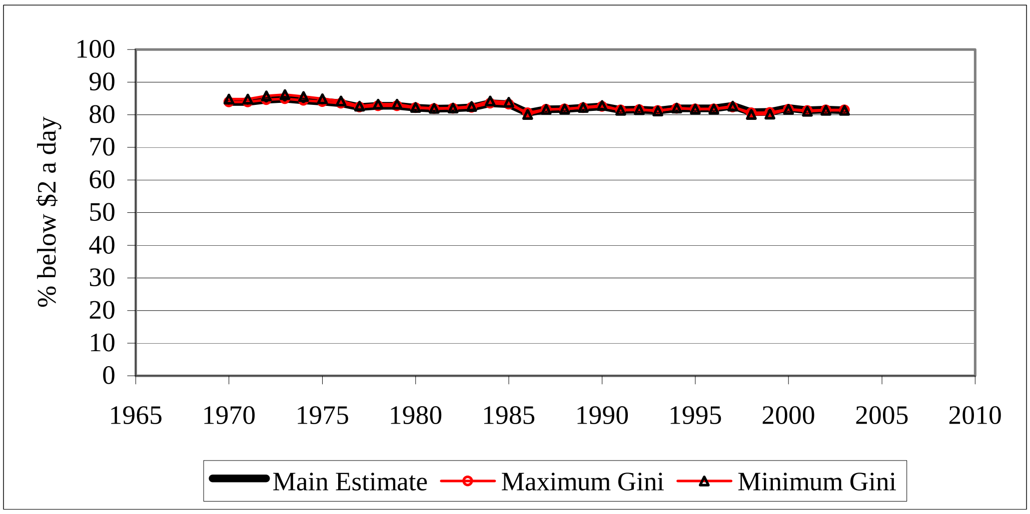


Figure 13, Headcount Poverty under different Distribution Assumptions
Ethiopia 1970-2005

($1 a day)

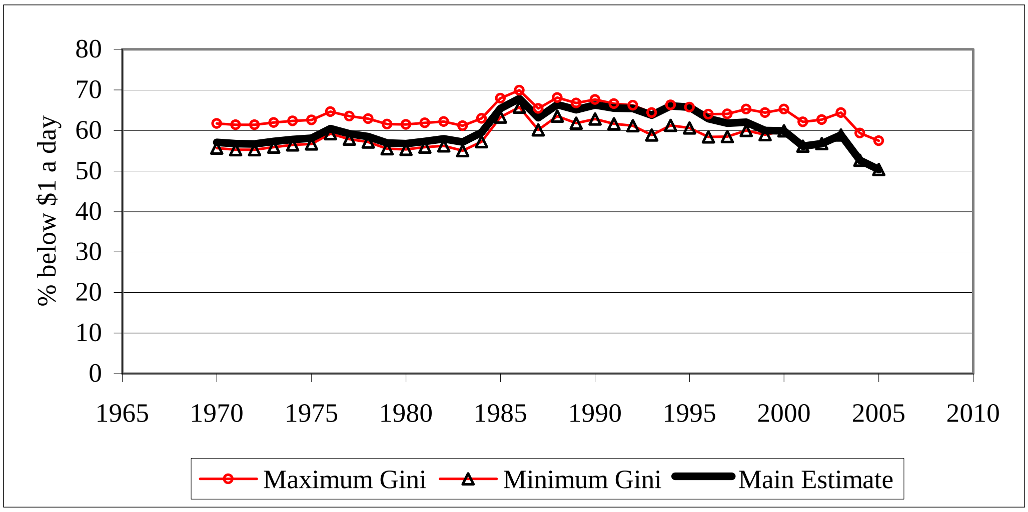


Figure 14, Headcount Poverty under different Distribution Assumptions
Ethiopia 1970-2005

($2 a day)

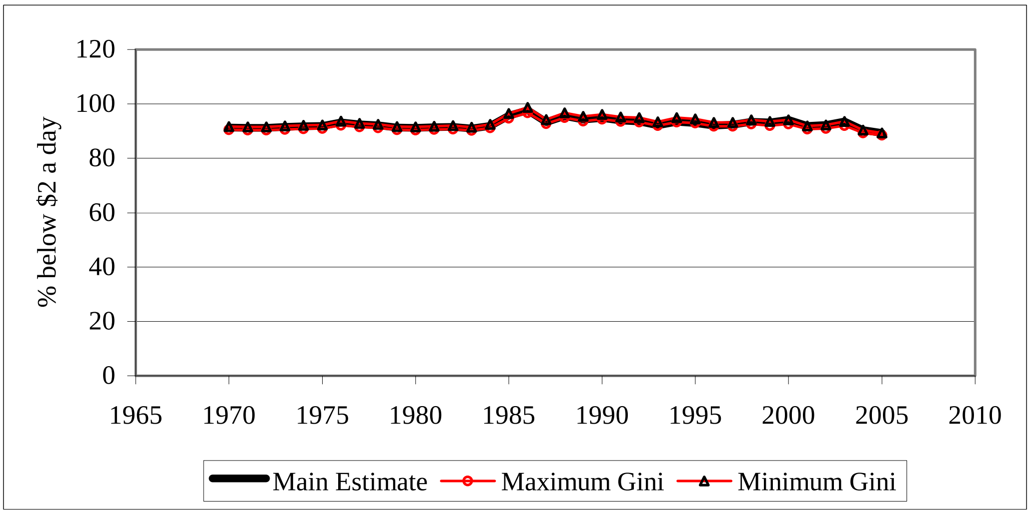


Figure 15, Headcount Poverty under different Distribution Assumptions
Lesotho 1970-2005

($1 a day)

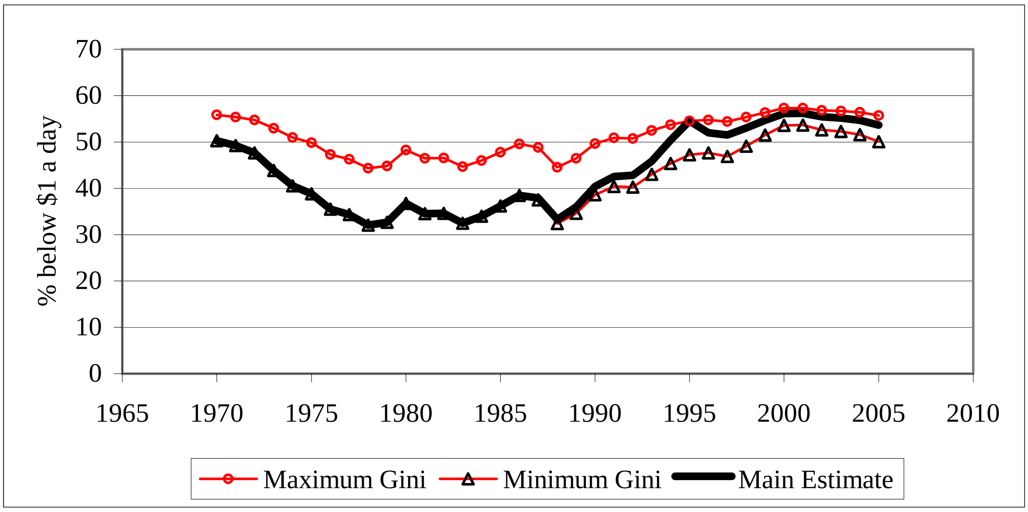


Figure 16, Headcount Poverty under different Distribution Assumptions
Lesotho 1970-2005

($2 a day)

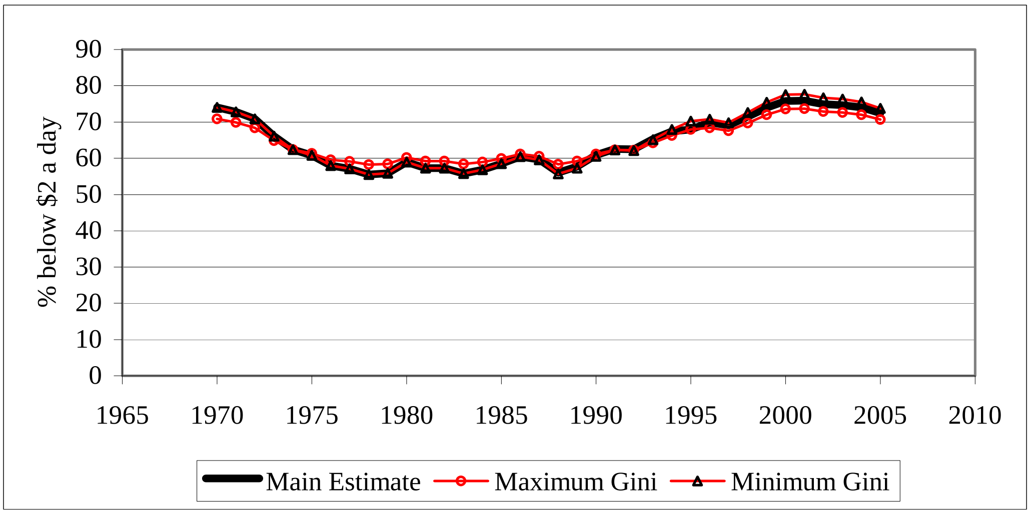


Figure 17, Headcount Poverty under different Distribution Assumptions
Madagascar 1970-2005

($1 a day)

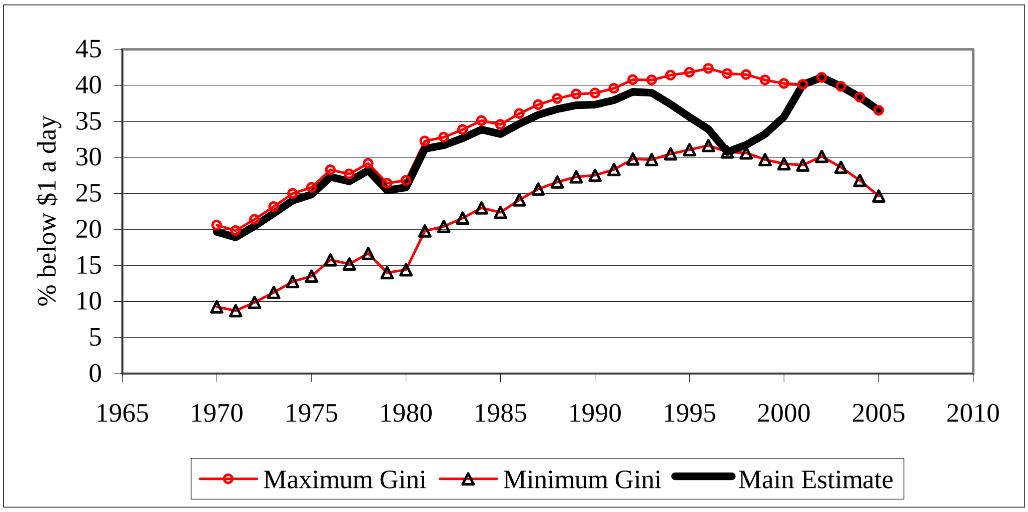


Figure 18, Headcount Poverty under different Distribution Assumptions
Madagascar 1970-2005

($2 a day)

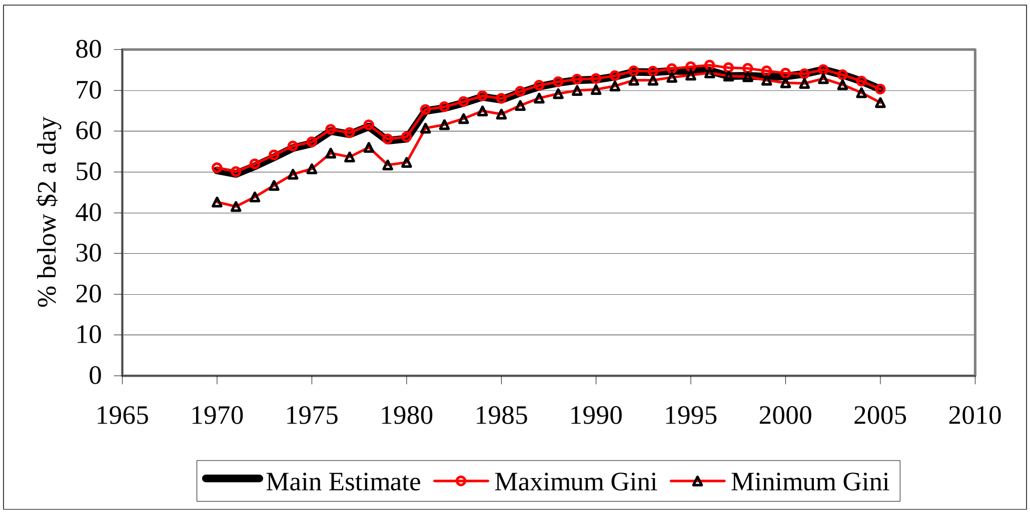


Figure 19, Headcount Poverty under different Distribution Assumptions
Mali 1970-2005

($1 a day)

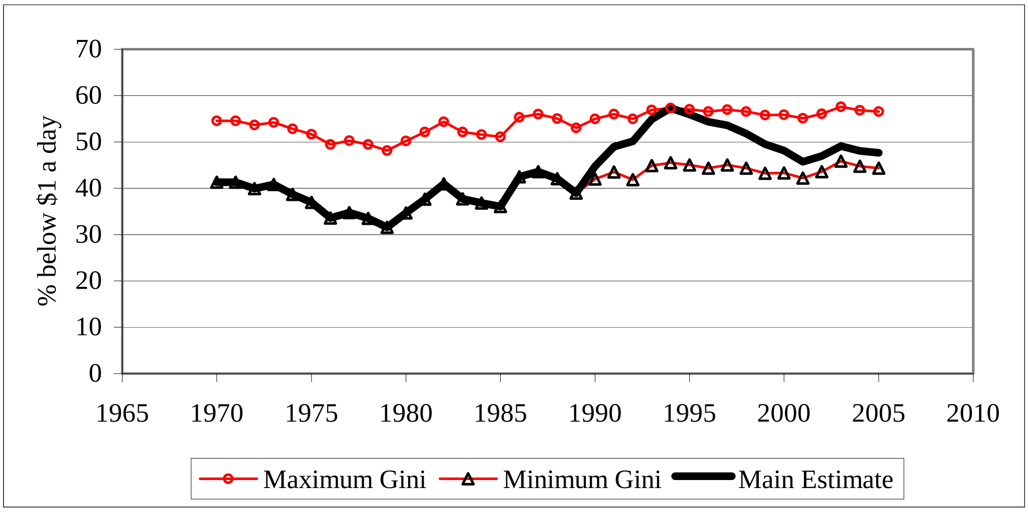


Figure 20, Headcount Poverty under different Distribution Assumptions
Mali 1970-2005

($2 a day)

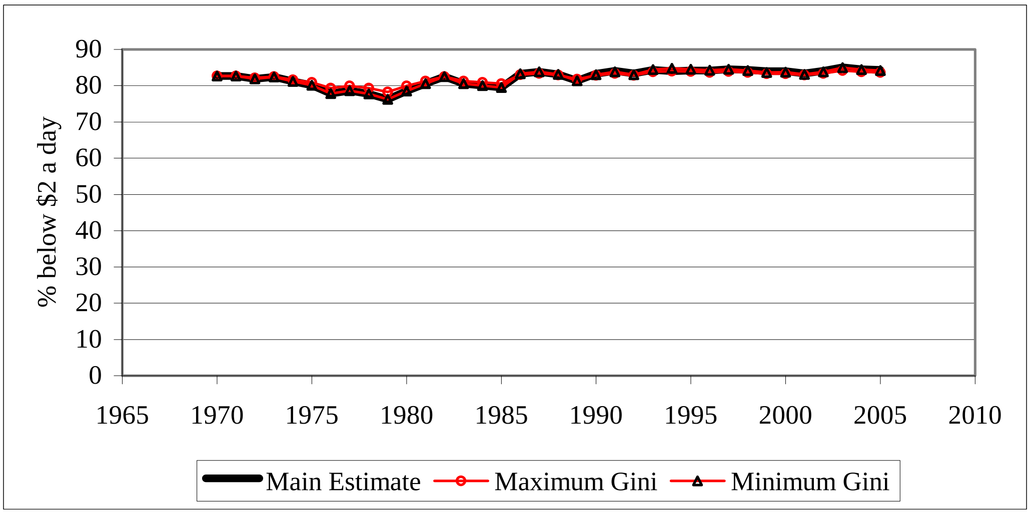


Figure 21, Headcount Poverty under different Distribution Assumptions
Mauritania 1970-2005

($1 a day)

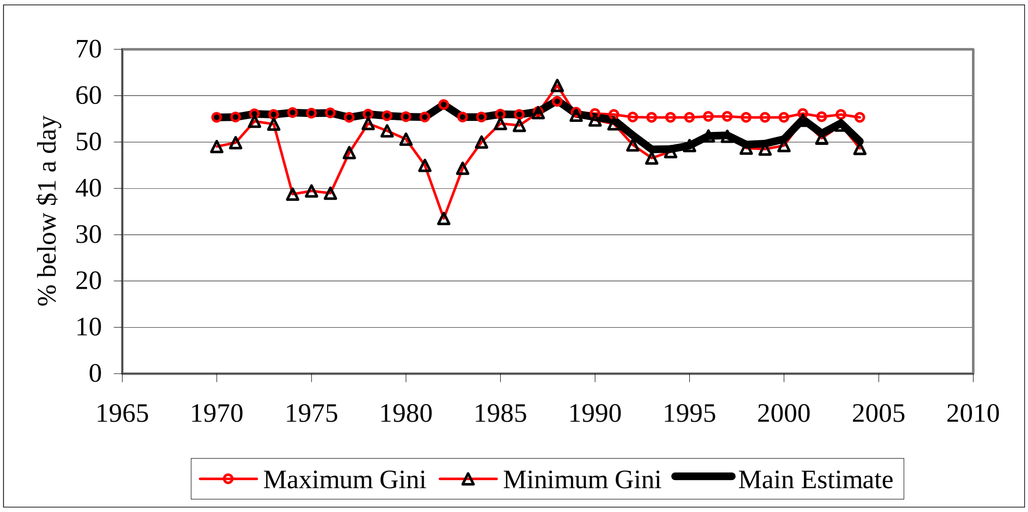


Figure 22, Headcount Poverty under different Distribution Assumptions
Mauritania 1970-2005

($2 a day)

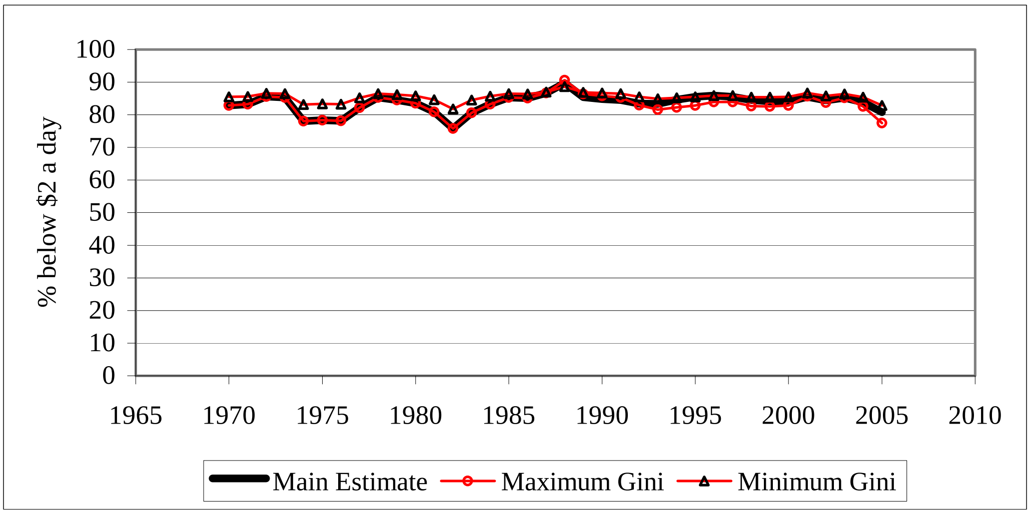


Figure 23, Headcount Poverty under different Distribution Assumptions
Uganda 1970-2005

($1 a day)

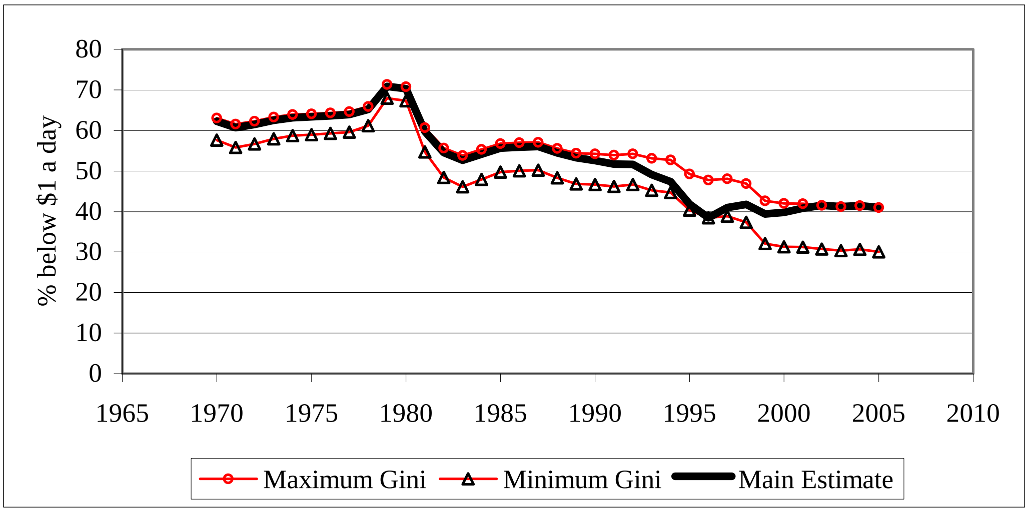


Figure 24, Headcount Poverty under different Distribution Assumptions
Uganda 1970-2005

($2 a day)

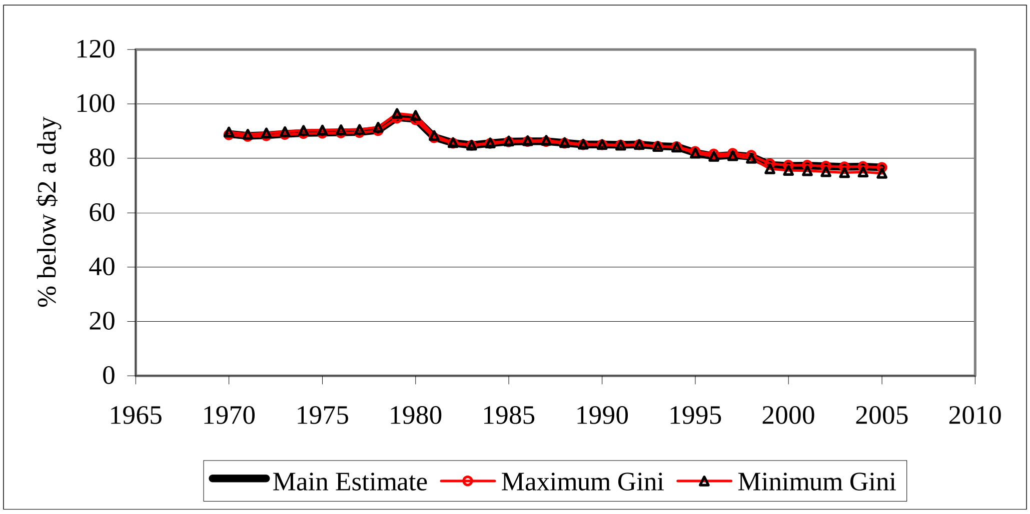


Figure 25, Headcount Poverty under different Distribution Assumptions
Zambia 1970-2005

($1 a day)

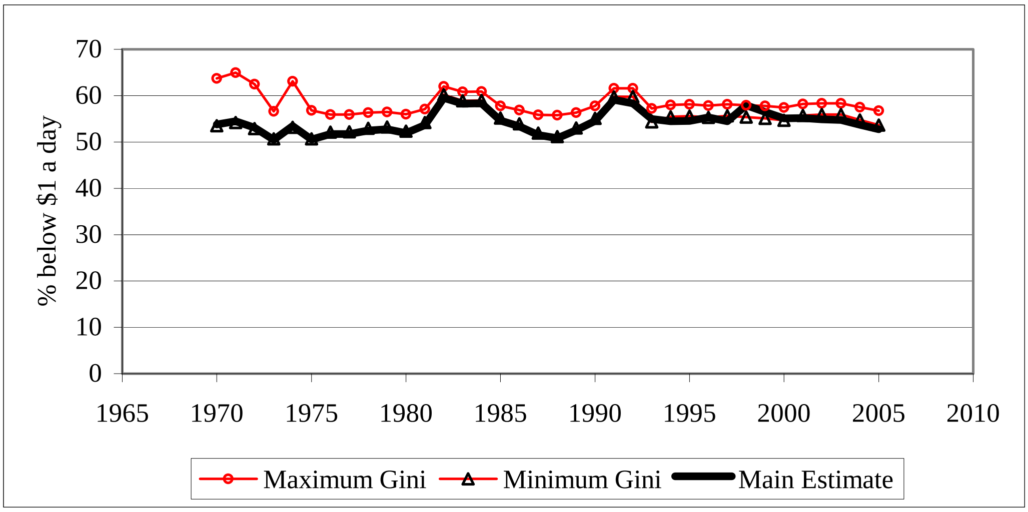


Figure 26, Headcount Poverty under different Distribution Assumptions
Zambia 1970-2005

($2 a day)

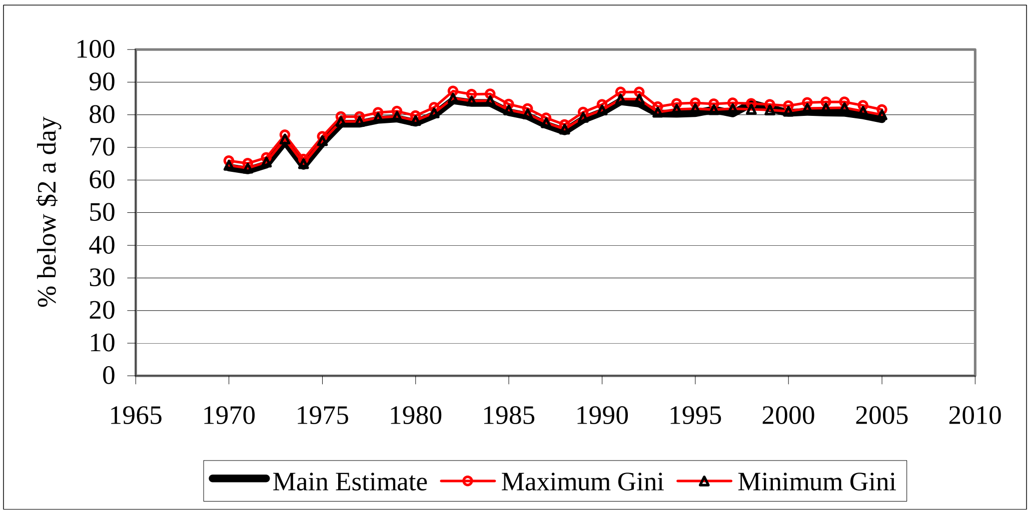


Table 1: Head Count Poverty in Least Developed Countries

		Per capita Consumption Expenditure			Head Count Poverty $1 a day poverty line		Head Count Poverty $2 a day poverty line		Head Count Poverty Minimum Calorie poverty line	
Country	Year	Survey	N. Accounts	Calibrated Survey Mean	New	W.B.	New	W.B.	New	W.B.
Benin	2003	714.7	1008.4	807.0	24.0	30.8	65.8	73.0	31.0	38.3
Botswana	1985.5	1052.5	1504.8	1085.6	32.8	33.3	59.5	61.3	37.4	38.5
Botswana	1993.9	1402.1	1857.5	1287.1	31.7	28.5	59.5	56.1	36.5	33.2
Burkina Faso	1994	653.9	617.0	588.7	56.2	51.4	83.2	80.1	62.0	57.2
Burkina Faso	1998	668.0	673.9	620.6	49.4	44.9	83.2	81.0	57.0	52.6
Burkina Faso	2003	752.2	638.3	600.7	42.3	28.7	81.1	71.3	50.3	36.1
Burundi	1992	525.8	n.a.	n.a.	n.a.	44.1	n.a.	85.1	n.a.	n.a.
Burundi	1998	482.9	n.a.	n.a.	n.a.	54.6	n.a.	87.6	n.a.	n.a.
Cape Verde	2001	2659.8	2860.9	1882.1	8.6	1.9	32.3	19.0	12.0	3.8
C.A.R.	1993	491.8	894.9	743.7	52.7	66.6	73.9	84.0	56.5	69.3
Ethiopia	1981.5	603.1	353.0	439.0	58.8	32.7	92.5	82.9	68.2	43.0
Ethiopia	1995	710.4	306.9	412.4	68.5	31.3	92.7	76.4	75.3	40.1
Ethiopia	2000	666.8	313.0	415.9	60.6	21.6	94.0	76.6	70.2	31.0
Gambia	1992	545.0	1089.2	852.0	31.9	53.7	66.0	84.0	37.6	60.0
Gambia	1998	1108.7	1089.0	851.9	38.6	27.9	65.6	55.9	43.2	33.6
Lesotho	1986.5	1223.2	1476.7	1069.6	35.3	30.3	60.0	55.5	39.5	35.1
Lesotho	1993	961.9	1251.3	942.7	43.7	43.1	64.9	65.7	47.3	46.7
Lesotho	1995	1444.0	1037.3	823.1	51.1	36.4	70.5	56.0	54.4	40.5
Madagascar	1980	601.7	1371.8	1010.4	25.2	49.2	57.9	80.3	30.6	55.4
Madagascar	1993	621.5	868.8	729.2	37.8	46.3	73.6	80.0	44.4	53.1
Madagascar	1997	512.3	843.7	715.2	31.6	49.8	70.1	84.7	38.2	57.1
Madagascar	1999	402.1	868.6	729.1	35.0	66.0	70.3	90.2	41.2	71.6
Madagascar	2001	483.4	890.0	741.0	41.6	61.0	71.4	85.1	47.0	65.6
Malawi	2004.2	860.9	730.3	652.1	36.8	20.8	77.6	63.0	44.8	27.6
Mali	1989	921.0	627.5	594.6	39.0	16.5	79.3	55.4	46.6	22.0
Mali	1994	389.6	529.9	539.8	58.4	72.3	84.1	90.6	63.8	76.6
Mali	2001	680.8	580.7	568.4	46.0	36.4	80.2	72.7	52.5	43.1
Mauritania	1987	563.2	394.0	462.6	56.3	46.7	86.3	79.4	62.5	52.8
Mauritania	1993	654.4	490.9	517.7	62.4	49.4	88.1	81.9	68.7	56.5
Mauritania	1995.5	726.4	464.3	502.7	48.6	28.6	85.4	68.7	56.1	34.9
Mauritania	2000	815.8	458.2	499.2	51.5	25.9	85.1	63.1	58.4	32.4
Mozambique	1996	615.5	630.0	596.0	47.5	45.6	81.8	80.9	54.6	52.8
Mozambique	2002	766.0	751.4	663.9	44.5	36.2	79.9	74.1	51.9	43.5
Niger	1992	564.8	589.5	573.3	40.7	41.7	83.3	84.1	49.6	50.7
Niger	1994.4	498.1	624.5	592.9	45.0	54.8	80.4	86.1	52.0	61.7
Rwanda	1984.5	564.5	638.8	601.0	30.4	35.0	81.5	84.2	40.6	45.8
Rwanda	2000	490.1	596.4	577.2	51.6	60.3	83.0	87.8	58.3	66.6
Senegal	1991	764.4	1261.0	948.2	37.0	45.4	64.6	73.0	41.8	50.4
Senegal	1994.5	845.9	1173.4	899.1	20.9	24.0	62.2	65.7	27.5	31.0
Senegal	2001	996.2	1458.5	1059.3	14.1	16.8	52.3	55.9	19.8	22.9
Sierra Leone	1989.5	587.6	462.7	501.8	60.7	57.0	78.6	74.4	63.8	59.9
Uganda	1989	533.9	704.5	637.7	51.8	87.7	82.7	97.1	58.0	91.1
Uganda	1992	535.6	708.6	639.9	51.9	90.3	85.8	98.1	59.6	92.3
Uganda	1996	605.0	876.1	733.3	39.9	87.9	80.1	97.5	47.9	91.4
Uganda	1999	669.9	1033.9	821.2	39.6	84.9	77.1	96.6	46.9	88.3
Uganda	2002	684.9	1109.9	863.6	42.1	82.3	77.7	95.7	49.3	85.9
Tanzania	1991	405.4	394.4	462.8	52.2	61.5	89.7	92.4	60.9	69.5
Tanzania	2000.4	437.2	378.0	453.4	54.4	57.0	89.8	90.2	62.6	64.9
Zambia	1991	455.6	426.7	481.3	57.0	60.4	81.4	82.1	61.4	63.3
Zambia	1993	344.4	568.6	561.6	54.8	73.6	80.0	90.7	59.5	77.5
Zambia	1996	377.2	538.4	544.6	55.8	72.2	83.5	91.5	61.6	76.9
Zambia	1998	454.3	536.1	543.3	58.0	65.7	83.6	87.8	63.3	70.6
Zambia	2004.3	492.1	555.0	553.9	54.6	60.0	81.8	84.9	60.0	65.0
Yemen, Rep.	1992	1812.2	n.a.	n.a.	n.a.	3.4	n.a.	19.9	n.a.	n.a.
Yemen, Rep.	1998	1037.5	n.a.	n.a.	n.a.	9.4	n.a.	43.5	n.a.	n.a.
Cambodia	1994	312.5	n.a.	n.a.	n.a.	82.0	n.a.	96.2	n.a.	n.a.
Cambodia	2004	436.0	n.a.	n.a.	n.a.	66.0	n.a.	89.8	n.a.	n.a.
Lao PDR	1992	702.2	n.a.	n.a.	n.a.	18.6	n.a.	74.9	n.a.	n.a.
Lao PDR	1997.2	728.8	n.a.	n.a.	n.a.	26.4	n.a.	73.2	n.a.	n.a.
Lao PDR	2002	695.0	n.a.	n.a.	n.a.	27.4	n.a.	74.2	n.a.	n.a.
Bangladesh	1983.5	577.9	570.1	562.4	28.3	26.2	85.4	84.0	39.0	36.6
Bangladesh	1985.5	632.9	595.2	576.5	29.4	22.0	84.2	79.9	40.4	32.2
Bangladesh	1988.5	548.9	609.0	584.2	30.6	35.4	83.5	86.2	41.2	46.7
Bangladesh	1991.5	553.3	653.3	609.0	26.6	33.7	80.6	85.3	36.5	44.6
Bangladesh	1995.5	614.5	733.6	653.9	28.1	32.9	78.4	81.9	37.9	42.9
Bangladesh	2000	562.2	800.1	691.0	26.4	41.3	74.8	84.2	35.5	50.9
Nepal	1995.5	660.8	751.3	663.8	34.1	34.4	77.2	77.9	42.5	42.8
Nepal	2003.5	969.0	894.0	743.3	40.1	24.7	76.3	64.8	47.5	31.8

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