Parametric Estimations of the World Distribution of Income

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We use a parametric method to estimate the income distribution for 189 countries between 1970 and 2006. We estimate the World Distribution of Income and estimate poverty rates, poverty counts and various measures of income inequality and welfare. Using the official $1/day line, we estimate that world poverty rates have fallen by 80% from 0.268 in 1970 to 0.054 in 2006. The corresponding total number of poor has fallen from 403 million in 1970 to 152 million in 2006. Our estimates of the global poverty count in 2006 are much smaller than found by other researchers. We also find similar reductions in poverty if we use other poverty lines. We find that various measures of global inequality have declined substantially and measures of global welfare increased by somewhere between 128% and 145%. We analyze poverty in various regions. Finally, we show that our results are robust to a battery of sensitivity tests involving functional forms, data sources for the largest countries, methods of interpolating and extrapolating missing data, and dealing with survey misreporting.

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(1) Introduction

Poverty, inequality, and growth of income are three subjects of major interest to economists, analysts, and policymakers around the world. Whether it is the rise of China over the past 30 years, the economic collapse and inequality explosion of the former Soviet Union 20 years ago, or the waves of anti-globalization protests and the push for aid to Africa in the past 10 years, the “facts” on these three variables are fundamental constants in almost every policy debate, and form the basis of heated debates when they are questioned. The United Nations has made halving the number of people living on less than $1 a day one of its eight Millennium Development Goals, indicating the high priority assigned to poverty reduction.

These three subjects represent different aspects of the same object: the distribution of income. Growth (of per capita GDP) usually relates to the percentage change of the mean of the distribution. Poverty relates to the integral of the distribution to the left of a particular poverty line. Inequality refers to the dispersion of the distribution.

However, although poverty, inequality, and growth are three different ways of looking at the same object (the distribution of income), researchers traditionally analyzed the three separately. They even used different data sources to analyze them. For example, when discussing issues related to growth, people used national accounts data to estimate the mean of the distribution (per capita GDP), and ignored distributional data available through thousands of surveys that had been conducted in many countries over time (Barro and Sala-i-Martin (1992); Quah (1996, 1997); Jones(1997); Kremer Onatski and Stock(2001); Bourguignon and Morrison (2002)) . Conversely, when researchers analyzed poverty or income inequality they tended to use survey data ignoring the numbers given by the national accounts (Milanovic (2002), Chen and Ravallion (2001, 2004), Chotikapanich (2007).)

We are not the first ones to merge survey and national account data to estimate characteristics of the WDI. Early work by the World Bank on poverty estimation also combined microeconomic surveys with national accounts data (Ahluwalia, Carter, Chenery [1979]). However, the World Bank decided to abandon this tradition in the mid-1990s and to anchor their data to the survey mean. In fact, they recommended that individual countries estimating poverty rates do the same thing so that countries like India, which had long anchored the survey distributions to the national account means decided to use both distributions and means from surveys. As argued by Deaton [2001], "no very convincing reason was ever given for the change". Authors such as Bhalla (2002), Chotikapanich et. al (1997, 2007) Bourguignon and Morrison [2002], Quah [2002], and Sala-i-Martin [2002a and b] also combine national accounts and survey data.

Sala-i-Martin [2006] uses a kernel density function to estimate the income distribution for each country-year between 1970 and 2006. This method sought to incorporate variation in income at the level of individuals rather than of countries or quintiles, while avoiding parametric assumptions on the country distribution of income. In this paper we build on Sala-i-Martin [2006] but, instead of using nonparametric kernel density functions to approximate each country/year income distribution, we assume that the functional form for the distribution of income is a parametric distribution, specifically a lognormal distribution in our base specification[2]. The level of per capita GDP is used to anchor the mean of the distribution income. The variance is estimated using least squares on the quintile shares reported in surveys. For each year, the lognormal individual income distributions for all countries are integrated to construct an estimate of the world distribution of income as well as various measures of poverty and inequality.

The literature has either made explicit functional form assumptions for the distribution of income, or approximated income distributions by flexible forms such as polynomials. Chotikapanich et. al [1997, 2007] and Quah (2002) use lognormal and more flexible specifications of income distributions, but have looked only at a few countries, or at a few years. Dikhanov and Ward (2001) use fourth-order polynomials to interpolate between income classes and estimate the world distribution of income for 1970-99, motivating their procedure by its precision in a class of income distributions. Part of our contribution is considering multiple classes of income distributions and arguing for the use of some distributions over others.

The empirical validity of the lognormal distribution has been tested widely. López and Servén [2006] use close to 800 country-year observations and conclude that

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[2] We allow for two exceptions to this rule: China and India. For these two countries, we estimate a mixture of two lognormals: one for the rural population and one for the urban population. More on this in Section 2.d.

the null hypothesis that per capita income follows a lognormal distribution cannot be rejected. Hill [1959], Cowell [1977], and Airth [1985] suggest that the upper tail of the distribution for the United States is thicker than implied by lognormality, specifically at the top 3-4 percentiles. This prompted attempts to fit more complex functional forms : truncated versions of the lognormal density (Metcalf [1969], Salem and Mount [1974]), alternative functional specifications (Fisk [1961], Salem and Mount [1974], Singh and Maddala [1976], McDonald [1984], Chotikapanich et al [2007]), and the five-parameter generalized beta function, which nests most of the previously proposed candidates for the functional forms like Pareto, lognormal, gamma, Weibull, Fisk and Singh-Maddala distributions (McDonald [1984]; McDonald and Xu [1995]; Parker [1999], Jenkins [2007]). Pinkovskiy [2008] uses lognormal mixtures in 37 data sets to allow for multimodality and finds that they perform no worse on average, and occasionally better, than do the generalized beta functions.

Using lognormal rather than kernel distributions has several advantages. First, the lognormal distribution has some nice theoretical foundations. Gibrat [1931] argued that the good empirical performance of the lognormal density could be rationalized under three conditions: (i) individual income for a particular period is given by the income of the previous period times a random component, (ii) the random component is a function of a large number of small factors, and (iii) each factor is independently distributed of others in the population. Under these conditions, the log of income is a sum of many independent random variables so it should be approximately normal according to the Central Limit Theorem. Since the kernel density estimator used by Sala-i-Martin (2002 a and b, 2006) is a mixture of 5 lognormals, the results of Sala-i-Martin (2006) could be reinterpreted as estimates under the assumption of separate Gibrat stochastic processes with equal variances for each quintile. A large body of research expanded Gibrat's work over the following decades. Kalecki [1945] realized that the variance of log income remained relatively constant so he allowed for the probability of negative shocks to be smaller at low income levels. Sargan [1957], Pestieau and Posen [1979] developed rigorous models that under fairly general conditions also yield lognormal distributions of earnings.

The assumption of multiplicative influence of small factors is also consistent with the assumptions underlying Mincer [1974] wage regressions in labor economics, in which log wage is an additive function of multiple variables, all of which account for a small amount of the variation in the wage, and all of which are presumably independent of the error term, which may be decomposed into additional determinants of the wage. The low R^2 reported by such regressions (e.g. Lemieux and Card 1998, Table 5b4, which reports an R^2 of 0.094 in a Mincerian wage regression with 46,279 observations) suggests that even the important variation in education and job tenure identified by Mincer explain only a small fraction of total variability in wages, making it plausible that log income is a function of many small shocks.

The second advantage is that parametric estimation offers ways to reduce the uncertainty of poverty and inequality estimates that kernel density estimation cannot. Since most household surveys have large sample sizes (many thousand), pure sampling error in the estimation of quintile shares is dwarfed by 1) uncertainty in the shape of the income distribution, and 2) bias in the surveys. By considering several plausible parametric forms and seeing which fits the data better, we can substantially reduce distributional uncertainty. While we make the lognormal distribution our baseline specification, we also consider the gamma distribution (analyzed by Salem and Mount (1974) as a better fit to U.S. household data than the lognormal), and the Weibull distribution (found to be the best two-parameter distribution for a group of surveys in OECD data by Bandourian et. al 2002).[3] Our results demonstrate that the lognormal distribution offers far superior fit to the data than do either of these common two-parameter alternatives, and that estimates obtained under the lognormality assumption are close to those obtained from the use of kernel density estimates.

A third advantage is that parametric estimation of the distribution allows us to correct for one of the potentially largest problems of the survey data: the bias in the surveys arising from the underreporting of the very rich and the very poor. It is widely known that sampling is hard at the very top and very bottom of the income distribution. The rich tend to not respond to surveys more systematically than the middle income (their

[3] Initially we also experimented with Pareto distributions but they fit the data much worse than the three alternatives we consider here, and the literature documents that they are useful only for modeling the extreme upper tail of the distribution.

houses are less accessible, their time may be more valuable) and they may tend to underreport a larger fraction of their income as they have more incentives to hide. The very poor, on the other hand, may be hard to interview (especially in poor countries) as they do not have identification or a fixed address. It may also be difficult to value the income of the very poor, as it often accrues in kind, rather than in currency. In Section 2.b. of this paper we suggest a methodology that may correct some of this problem under a broad variety of patterns of misreporting, conditional on the distributional assumption.

In our paper, we also check if the conclusions of Sala-i-Martin [2006] are robust to a general sensitivity analysis. We expand the coverage of Sala-i-Martin [2006] to more years (from 1970-2006 rather than 1970-2000) and include 189 countries rather than 138, representing 97.9% of the world's population.[4] We also use an updated and more detailed version of the WIDER-DS database described in Deininger and Squire (1996), which allows us to obtain more comparable data on income distributions over time in a given country. Furthermore, as the performance of China and India is a crucial part of our story, we experiment with multiple alternative specifications, notably breaking down China and India into rural and urban components to better capture the distributional dynamics of these two key countries. We also experiment with different ways to impute distributional information for countries and years for which surveys are not available. Finally, we consider alternative estimates of PPP-adjusted GDP aside from the standard estimates of Heston, Summers, and Aten (2006), and use them to argue that the most important task in an account of convergence is to correctly describe the evolution of country GDP, with within-country distributions playing a secondary role.

Policy discussions of a tradeoff between growth and inequality often struggle to specify a measure of "welfare" that could be used to judge whether a particular reform that increases growth and inequality together is, on net, beneficial. Sala-i-Martin (2006) has documented that the world experienced both GDP growth and a decline in inequality, which increase any sensible measure of welfare, since growth is taken to be good, and inequality is taken to be bad. In this paper, we cease being agnostic on the welfare measure, and present reasons for adopting a specific one: Atkinson's (1970) welfare

[4] The U.S. Bureau of the Census International Data Base estimates world population in 2006 to have been 6,554 million people at midyear, with the midyear estimate for 2005 being 6,476 million. Hence, our coverage is nearly universal.

index, which can be interpreted as the certainty equivalent of the income distribution considered as a lottery. We argue that sensible variations of this measure of welfare have been moving relatively similarly together, and have not only been growing, but have been growing at increasing rates. We also document the growth in welfare over the period 1970-2006 and find it to be staggering. Finally, we show that the same contentions hold if countries are judged to be the relevant communities for computing welfare, so welfare is an average of all the country distribution certainty equivalents.

The rest of the paper is organized as follows. Section 2 describes the data and the methodology used to estimate the country as well as the world distributions. Section 3 makes some theoretical considerations regarding inequality and welfare indexes. Section 4 describes the baseline distributions for the largest countries, the regional distributions and the world distribution of income. Section 5 analyzes the evolution of poverty. Section 6 discusses various measures of inequality and welfare. Section 7 presents regional analysis. Section 8 discusses some sensitivity analysis. Finally, Section 9 concludes.

(2) Data and Statistical Procedure

(a) Least-Squares Procedure for Obtaining Distributional Parameters from Surveys

We first estimate distributional parameters for country-years for which we have income distribution data in the form of a Gini coefficient and five quintile shares. We use the assumption that the income distribution for each country-year is of a specified parametric form to derive the expressions for the population quintile shares. These formulas are very useful in that they express the cumulative quintile shares as functions of the scale parameter alone. We then estimate the scale parameter by the value that minimizes the sum of squared deviations between the population cumulative quintile share expressions and the actual data. This least-squares method is common in the literature (e.g. Chotikapanich et. al. (2007)), and should generate a consistent, asymptotically normal estimator of the scale parameter, since the sample quintile means are consistent, asymptotically normal estimators of the population quintile means [see Moore (1968)], and the scale parameter estimator is an implicitly defined continuous function of the sample quintile shares. Since all other estimators that we use are continuous functions of the scale parameter estimator and the national accounts means (which are assumed to be the true mean income values for the respective country-years), all our estimators of the distributional parameters and poverty and inequality measures should be consistent and asymptotically normal. We then estimate the location parameter of the parametric distribution from the scale parameter and the national accounts mean, and thus define the distribution of income for each country-year completely. This allows us to get point estimates of the poverty and inequality measures for each country-year, and hence for the world as a whole for any year.

An alternative and often used method (Quah 2002) is to compute the scale parameter by inverting the Gini coefficient. If our distributional assumptions are correct, these two methods should be identical, as the Gini coefficient is also a continuous function of the scale parameter of each distribution under consideration. We have computed some poverty and inequality estimates using this method, but we have chosen to retain the quintile share method for our baseline specification in order to be able to perform the survey misreporting adjustment described below, and to ensure greater comparability with Sala-i-Martin (2006), which did not use Gini data.

After computing the least-squares scale parameter of each distribution under consideration, we use the distributional assumption to compute the Gini coefficient resulting from the scale parameter. We use these coefficients both as our estimates of the population Gini coefficients, and as data for accounting for inequality in country-years for which surveys are not available, since the Gini coefficient is a one-dimensional distribution-independent summary of the inequality of a distribution.

(b) Estimation of Distributions for Country-Years with No Inequality Data

Following the current literature, we break up our sample of countries into regions, roughly corresponding to the World Bank region definitions.[5] Following Sala-i-Martin

[5] The regions are: East Asia (excluding Japan and Hong Kong), South Asia (the Indian subcontinent including Afghanistan), Sub-Saharan Africa, Middle East-North Africa, Latin America (including Caribbean), Eastern Europe (Soviet Bloc satellites), the (former) Soviet Union, and the OECD (North America excluding Mexico, Western Europe, and Japan) . There are a few non-OECD countries with high income (Cyprus, Israel, Hong Kong, Macao and Singapore) but they are negligible for the analysis.

(2006), we also divide the countries into 3 groups according to survey availability. For each group, we use a separate procedure to interpolate, extrapolate or impute the Gini coefficients for country-years with no inequality data. After we have obtained Gini coefficients for all country-years with GDP data, we use the Gini and the GDP to solve for the scale and location parameters of all income distributions.

Group I – countries with several years of distribution data

For each country in Group I, we calculate the Gini coefficients of years with no income distribution data that are WITHIN the range of the set of years with data by interpolation of the implied Gini time series for the country, where the implied Ginis have been derived from the least-square minimizing scale parameters. Since there is no interpolation method to use that is suggested by theory, we experiment with three methods that satisfy an appealing property: the interpolated series between two data points is a monotonic function in the direction of the data points. This property is implied by the assumption that the survey data captures all turning points of the Gini series for all countries with multiple data points, which may be plausible.[6] All these methods imply virtually identical poverty and inequality measures, whether for the world or for regional aggregates. Calculating Gini coefficients for years with no data that are OUTSIDE the range of the WIDER surveys is more difficult, as we do not even know the direction of changes in inequality, so our previous method does not work. We therefore use one of the three extrapolation methods described below: projecting Gini coefficients horizontally into the extrapolation period, projecting Gini coefficients linearly, or a mixture of the two.

Group II – countries with only one year of distribution data.

We keep the single year of data, and impute the Ginis for other years to have the same deviations from this year as does the average Gini time series taken over all Group I countries in the given region, relative to the year for which we have data for the given country. Thus, we assume that the country's inequality dynamics are the same as those of

[6] It may be argued that surveys are rarely conducted during extreme rises in inequality because these are accompanied by social unrest, and if so, we do not record these jumps in our estimates. However, since we are concerned with inequality trends, our task is to record persistent rises in inequality rather than the temporary effects of crises. Presumably, surveys conducted with regularity should capture a permanent change in the level of inequality.

its region, but we use the single data point to determine the level of the country's income distribution.

Group III – countries with no distribution data.

We impute the average Gini time series taken over all Group I countries in the given region.

(c) Reconstruction of GDPs of Special Countries

For any GDP series, we perform several aggregations (or disaggregations) in order to analyze urban/rural China and India, the Soviet Union, Germany, and Czechoslovakia.

To disaggregate China into urban and rural components, we use rural population share and rural and urban mean income data (in yuan) from Chen-Ravallion (2007) and from the Chinese Statistical Yearbook. To take advantage of the different time ranges of the two sources, we construct hybrid series for the rural and urban mean incomes by regressing the Chen-Ravallion series on the Statistical Yearbook series and extending the Chen-Ravallion series using the predicted values. We are then able to compute the fraction of GDP held by the rural population in China for the years 1978-2005, and we extend this series by extrapolation on the basis of the trends in the first two and last two observations.

To disaggregate India, we use rural and urban survey mean income data from POVCAL, and rural population share from the World Bank. We interpolate both mean income series by means of piecewise cubic splines, and construct the fractions of national GDP held by the urban and rural populations from these series. We use these fractions to construct urban and rural GDPs from the sources of GDP data that we use.

To construct the USSR aggregate for 1970-1989, we calculate Soviet GDP as a population-weighted average GDP of all the constituent republics in 1990, and use the growth rates from PWT 5.6 to impute Soviet GDP for the 1970s and 1980s.

To disaggregate Germany into East and West for 1970-1989, we compute the East German GDP by using the fraction of all-German GDP held by East Germany and East German growth rates in the PWT 5.6 dataset.

To aggregate Czechoslovakia, we compute the Czechoslovak GDP in 1990 from Czech and Slovak GDPs, and use Czechoslovak growth rates from PWT 5.6 to compute Czechoslovak GDP for the years 1970-1989.

(d) Sensitivity to GDP

We compute the world distribution of income for 3 different sources of GDP. These are 1) the Penn World Tables data from the 6.2 edition, 2) World Bank data from 2007, and 3) data from Angus Maddison's website, dated 2007. We normalize all the GDP data by scaling the World Bank and Maddison data to coincide for U.S. GDP in 2000. Hence, we express all figures in constant 2000 international dollars, as does the PWT.

We also extend both the PWT62 and the WB GDP series to span the period 1970-2006. The PWT62 series spans the period 1970-2004, whereas the WB series spans 1975-2006. For years in which GDP is available from only one series, we impute its growth rate for the other series. For some countries, GDP is not available for the last few years for any series, so rather than dropping these countries from our analysis, we forecast GDP in these years by assuming that the growth rate of GDP is a 4-year moving average. The effects of this forecasting procedure are very small; for the PWT62 series, only the years 2004-2006 are affected, with 1-3% of the world population affected each year.

(e) Income Surveys

We divide the surveys in the WIDER-DS database into groups according to the country in which the survey was conducted, and according to the survey description provided in the WIDER-DS database. Specifically, all the surveys in a given survey group have the same area cover, population cover, age cover, income sharing unit, unit of analysis, equivalence scale, definition of income, primary source and secondary source of the survey. We select the surveys from the WIDER-DS database for each country by finding the set of survey groups that gives the longest time coverage, while having all groups be temporally disjoint (with overlap of at most one year between successive groups), and having all groups be based on the same definition of income, if possible. If we choose to use consumption surveys, we perform an adjustment procedure that parallels Bhalla (2002), which is described in Appendix C. For African countries, we include all surveys regardless of income concept, since survey coverage is sparse. For China and India rural and urban surveys, we use income and consumption data from the World Bank POVCAL database.

The WIDER-DS dataset has been criticized for its sparseness of coverage and for the potential comparability problems between its surveys owing to differences in the definition of income (gross or net) and to differences in adjustments for household size (Atkinson and Brandolini 2001). While these may be severe problems for estimating the level of world inequality in a particular year, these problems are far less serious when analyzing changes in inequality across time. The single most important danger of survey heterogeneity would be if surveys tended to switch to reporting a more equally distributed type of income (net income over gross income, for instance) over time within countries. However, this problem does not occur for the largest countries in our sample (China, India, Indonesia, Bangladesh, Pakistan, Nigeria, Ethiopia, and the US), which account for an overwhelming proportion of the world population, so we do not believe that income concept heterogeneity is a serious problem in our calculations.

It is particularly important for our purposes to correctly estimate the changes in income distribution for the two largest fast-growing countries in the sample: China and India. Since we have survey and GDP data on the rural and urban sectors of both countries, and since development often proceeds differently in urban and rural parts of a country, we find it important to consider these sectors separately. We experiment with three options: 1) China and India are treated as unitary countries, 2) China and India are broken up into rural and urban sectors, and only income surveys are used for China, and 3) China and India are broken up into rural and urban sectors, and both income and consumption surveys are used for China. Including Chinese consumption surveys violates the spirit of our survey-selection methodology, but may be warranted on the grounds that the surveys move together, and we should make an effort to incorporate all the information about China that is available. We use option 2 in our baseline as a compromise between methodological consistency and maximal incorporation of information.

Overall, we use 1069 surveys, which directly cover over 25% of the world population in an average year in the baseline case.[7] Since we have 193 countries or

[7] Of these 1069 surveys, 85 lie outside the period of interest, and are used in order to replace extrapolation with interpolation for the early part of the period. These surveys tend to be post-independence surveys in Africa, or republic-wide studies in the USSR in the late 1980s. Hence, we have 984 surveys in the period of interest proper.

subdivisions of countries covered by separate surveys (the 191 countries, plus rural components for China and India), we have on average 5.5 surveys per country, or one survey every six country-years of the sample period. Given the inconsequentiality of the interpolation method for the estimates (which we show in section 8.a), a better measure of the quality of the survey coverage is the percentage of the world population in each year that is either covered by surveys directly or is subject to interpolation. This number rises to 85% or more for all years from 1980 to 1998 for the baseline case. Under our alternative survey selection regimes for China and India, coverage is even better: it is over 64% before 2003 if China and India are treated as single countries, whereas it is over 64% from 1980 to 2003 if consumption surveys for urban and rural China are considered.

(f) Sensitivity to the Interpolation Method

We compute estimates for three methods of interpolation: 1) nearest-neighbor interpolation, 2) linear interpolation, and 3) piecewise-cubic Hermite polynomial interpolation (PCHIP). All these methods satisfy a monotonicity assumption, by which interpolated values change (weakly) monotonically, without leaving the interval defined by the true values of the measure between which interpolation takes place. The purpose of varying interpolation methods is to demonstrate that the main results of falling poverty and inequality are largely invariant to changes in assumptions about years for which we do not have surveys. We use PCHIP in our baseline specification, as it allows Ginis to vary smoothly from year to year, without introducing arbitrary kinks or discontinuities.

(g) Sensitivity to the Extrapolation Method

We experiment with three methods of extrapolation: 1) remaining agnostic about changes in inequality and assuming that the Gini coefficient remains constant at its latest (earliest) value for the extrapolation period, 2) assuming that the trends closest to the extrapolation period in the survey data continue unabated and extrapolating linearly using the slope of the Gini coefficient between the last two data points, and 3) a mixture of the two methods in which we assume the Gini coefficient to remain constant into the extrapolation period, except if the last two years before the extrapolation period both have true survey data. The last method is a way of taking account of recent trends only if they are "strong." For some country-years, the latter extrapolation methods lead to the Gini coefficient violating its range in the unit interval. To keep all Ginis within historical bounds while allowing them to potentially rise or fall a large amount, for the countries for which extrapolations violate the range of the Gini in the survey data (from 0.17 to 0.81), we downweight in absolute value the changes in the Gini by a factor of δ^i, where *i* is the distance between the given year and the last (or first) year with survey data, and δ is a discount factor chosen to make the Gini coefficient attain the boundary of the empirical range in 2006 (or 1970 if we are extrapolating backwards).[8]

To avoid unnecessary proliferation of variations, we vary extrapolation methods and interpolation methods together: we use PCHIP splines with horizontal projection, linear interpolation with linear extrapolation, and nearest-neighbor interpolation with the hybrid method. As it will be shown that the interpolation methods are largely equivalent, we consider that no generality is lost by so doing.

(h) Sensitivity to Functional Forms

We compute estimates for three types of parametric distributions – the lognormal, gamma and Weibull – as well as for kernel density estimates from Sala-i-Martin (2006). These distributions were chosen for their tractability and for their popularity in income distribution analysis. All our parametric distributions come from two-parameter location-scale families, which allows us to use the estimation framework described above. In addition to computing worldwide estimates for all these distributions, we also consider estimates that would result from different countries possessing distributions with different functional forms. We assign to each country the distribution that minimizes the sum of squared deviations between the survey cumulative quintile shares and the cumulative quintile shares of the optimal parametric distribution across all three functional forms across all available surveys.[9] We present estimates from the resulting "optimal" world distribution along with the other estimates.

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[8] Informal analysis of the Gini coefficient time series resulting from interpolation and extrapolation suggests that option (1) presents more plausible inequality dynamics than does option (2); the extreme values of the Gini in the series are attained far more frequently in the extrapolation period using linear extrapolation than using nearest-neighbor extrapolation. Therefore, linear extrapolation should be considered as a "sensitivity analysis" for extreme changes in inequality based on recent trends.

[9] For Group 3 countries, we use the distribution that is most frequently optimal among all other countries.

(i) Survey Misreporting Adjustment

The fact that we are working with parametric distributions allows us to go further than Sala-i-Martin (2006) by explicitly controlling for a wide range of potential misreporting problems in the surveys. It is known (Deaton (2005)) that concerns with household surveys often arise from their inability to assess the income of very poor or very rich people, either owing to income censoring at the top, or to difficulties in converting in-kind income into monetary equivalents. However, under the assumptions that 1) individuals are placed correctly into quintiles, and 2) measurement error is present only for individuals in the first or last quintile, the ratios of the middle three quintiles to the sum of the middle three quintiles are measured correctly, since these statistics involve only the observations on the middle three quintiles. Under the assumption of known parametric form of the distribution, it is easy to compute these quintile share ratios, and to estimate the scale parameter of the distribution as the minimizer of the sum of squares of the deviations of these expressions from their values in the data. We will do this in section 8.d.

(j) Summary: Baseline Specification

We present our results by considering variation on one parameter from a baseline specification. Our baseline estimates involve the following assumptions:

1. We use GDP data from PWT 6.2
2. We break up China and India into urban and rural components, and use POVCAL surveys for within country inequality. For China, we use the rural and urban income surveys only; we exclude the consumption surveys.
3. We use piecewise cubic splines to interpolate between available survey data, and extrapolate by horizontal projection.
4. We assume that the distributions in all country units (countries or rural / urban subdivisions) are lognormal, and compute scale parameters from quintiles.

These assumptions veer towards avoiding making too many assumptions or comparing potentially incomparable series. We use quintiles in order to be able to assess the effect of the survey adjustment procedure. The lognormality assumption and the use of quintiles are also most consistent with the work of Sala-i-Martin (2006).

(3) Inequality and Welfare: Theoretical Considerations

While the headcount ratio is the prevalent measure of poverty, there exists no parallel focal measure for inequality. We therefore present several indices that we consider to be particularly well-founded as measures of inequality, as well as several widely cited indices. Specifically, we consider percentile ratios, the Gini coefficient, the Atkinson indices, and the generalized entropy indices, which include the Theil index and the Mean Logarithmic Deviation.

The Atkinson inequality indices arise as a natural extension of the Atkinson welfare measures. Since there is no unique basis for making interpersonal comparisons of welfare, one can argue that these (and all other) welfare measures are arbitrary; however, the Atkinson welfare measures have a non-arbitrary interpretation that seems compelling. The Atkinson welfare index (or equally-distributed income) is given by:

$$Y = \left(\int x^{1-\gamma} dF(x)\right)^{\frac{1}{1-\gamma}} = E(X)\left(1 - A(\gamma)\right)$$

where *x* is income, *F* is the distribution of income, and γ is the coefficient of inequality-aversion of the society.[10] The Atkinson welfare measure immediately suggests a measure of inequality: the ratio between the "risk premium" and the expected value of the income distribution, which is $A(\gamma)$ in the formula above. The Atkinson inequality index satisfies the conventional axioms of inequality measures -- anonymity, aversion to mean-preserving spreads (the principle of transfers) and invariance both to population and income scale. As is described in Atkinson (1970), the Atkinson welfare index can be viewed as the certainty equivalent for a person with a CRRA utility with risk aversion parameter γ of a lottery over payoffs, in which the density is equal to the distribution of income. Hence, the Atkinson welfare index is the sure income a CRRA individual would find equivalent to the prospect of being randomly assigned to be a person within the community with the given distribution of income, and provides a representation of a CRRA individual's preferences over joining societies with given distributions of income "behind the veil of ignorance" of her position within them. This rating presumes that the good society is one that would be chosen by rational (expected utility-maximizing) agents

[10] The index for $\gamma = 1$ is the limit of the general expression, which is $\exp\left(\int \ln(x)\, dF(x)\right)$

under the veil of ignorance, which draws on the ideas of Vickrey (1960) and Harsanyi (1955). The insight of the Atkinson approach is a recognition that the growth-inequality tradeoff may be viewed as a risk-return tradeoff (at least if income is the only desideratum and if the income distribution is regarded as stable), which can be analyzed using the standard tools of economics. Any individual evaluator can use the Atkinson welfare index representing her risk aversion to assess her preferences over joining the given societies under the veil of ignorance.

The adaptability of the Atkinson index to the preferences of the evaluator may be seen as a shortcoming because the risk aversion coefficient γ is left undetermined. As an alternative, we consider the most famous inequality index, the Gini coefficient. The Gini coefficient has been used since the 1910s (specifically Gini (1912)), but it has been more recently endorsed by Amartya Sen as a distribution-free inequality index that represents the views on inequality of a society with very general distributional preferences. Specifically, the Sen welfare index (Sen, 1976), which is given by

$$S = E(X)(1-G)$$

with G being the Gini coefficient, represents the welfare judgments of a society in which the Pareto weights of individuals depend on their rank by income, are determined by the rule that the differences between the weights of successively ranked individuals are the same (Sen, 1974), which reflects a strong form of inability to make judgments about income magnitudes. The Gini coefficient is better known than Atkinson's measures, but is less tractable mathematically.

Related to the Atkinson indices are the generalized entropy (GE) indices, defined by the formula

$$\mathrm{GE}(\alpha) = \frac{1}{\alpha(1-\alpha)}\left[1 - \frac{\int x^{\alpha} dF}{\mu^{\alpha}}\right]^{11} \text{ for all real } \alpha$$

For $\alpha < 1$, for each $\mathrm{GE}(\alpha)$, there exists an ordinally equivalent Atkinson $A(1-\alpha)$ index. The GE family includes the Theil index (GE(1)), the mean logarithmic deviation

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[11] For $\alpha = 0, \alpha = 1,$ and $\gamma = 1$ these indices are given by:

$\mathrm{GE}(0) = -\int \ln\left(\frac{x}{\mu}\right) dF, \mathrm{GE}(1) = \int \frac{x}{\mu} \ln\left(\frac{x}{\mu}\right) dF,$ and $A(1) = 1 - \frac{\exp\left(\int \ln(x) dF\right)}{\mu}$

(GE(0)), and the square of the coefficient of variation (GE(2)). One attractive feature of the GE family is the additive decomposability of the indices into inequality between and within subgroups, making it an ideal tool for analyzing changes in between-country inequality as opposed to within-country inequality. Between-country inequality is the inequality there would exist if all citizens within each country had the same level of income; Within-country inequality is the inequality there would exist in the world if all countries had the same level levels of per capita income but kept their different sizes and within-country dispersions (and it tends to be a weighted average of each country inequality measure, where the weights are proportional to the size of the country).The drawback of GE indices is that their range varies with α, making them more difficult to interpret than Atkinsons.

Theoretical Parameter Restrictions

We begin by noting that while GE and Atkinson indices can be defined for all parameter values α and γ, we find it sensible to restrict the sensitivity analysis to indices with parameters in the unit interval. Indices outside the unit interval are statistically fragile, and have pathological properties that challenge our intuition of inequality comparisons. These problems are particularly acute when gamma or Weibull distributions are used, owing to the fact that not all their negative moments exist. Specifically, it can be shown that if for any ¿, the researcher is given the income distribution on an interval $[a, M]$ containing $1-\varepsilon$ of its mass, and is in addition given the mean of the entire distribution, the researcher cannot bound an inequality measure with index outside the unit interval from above (below its definitional bound). The proof of this proposition is presented in Appendix A. These considerations show that GE and Atkinson indices with the relevant coefficient outside the unit interval cannot be bounded from above using quintile shares, and it is obvious that they cannot be bounded from above without knowing the support of the distribution of income.[12] Therefore, without assumptions that *F* declines sufficiently rapidly, these indices can vary dramatically on the basis of only a few observations in a survey. Hence, their estimation without

[12] It is easy to see that knowledge of the Gini coefficient cannot bound them either, as any Gini value is compatible with atoms at zero, or with arbitrarily high incomes of a small share of the population.

distributional assumptions must be very difficult. These indices are particularly unsuitable given the available data in the Deininger-Squire database, as it adequately represents only quintile shares and Ginis.

Besides the practical problems of estimating such indices, there are theoretical difficulties with their implications. It is clear from the proof that not only are these indices extremely sensitive to outliers in the data (which does not contradict the intuitive notion of inequality), but they are also extremely sensitive to the distribution of income within these outliers. Graphically, these indices imply either that an unbounded increase in inequality may be achieved by redistribution within the top $\varepsilon\%$ for ε arbitrarily small (think of Warren Buffet donating most of his income to Bill Gates), or that an unbounded increase in inequality may be achieved by redistribution within the bottom $\varepsilon\%$. While the first implication may be sensible if income is seen as an asset of political power (consolidation of power in single hands may be dangerous), it does not seem sensible if inequality is dangerous because of the potential for envy or a stimulant for crime (as in Sala-i-Martin (1994)). For the Atkinson family of indices, the second implication is particularly pernicious given the interpretation of the index as an expected utility rating advanced by Vickrey (1960) as is discussed above. It suggests that individuals do not tolerate positive probabilities of receiving zero income, which is inconsistent with individuals taking potentially mortal risks when it is feasible to avoid them, such as enlisting in a campaigning army.[13] Therefore, there exist both theoretical and practical reasons for restricting the coefficients of GE and Atkinson indices to the open unit interval.

We encounter a manifestation of this difficulty when using the gamma and Weibull distributions to model income inequality. The GE and Atkinson indices of these distributions with parameters outside the unit interval are undefined for small positive values of the scale parameters (they involve evaluating the gamma function at negative arguments), and rapidly approach their maximum values when the scale parameters approach these thresholds. Figure 45 shows the Atkinson welfare index for the world for $\gamma = 1.5$, for the Gamma distribution. The bizarre dips in 1975, 1984 and 1992 are

[13] All CRRA functions with $\gamma \geq 1$ have this undesirable property. While we can often innocuously ignore this problem when incomes are far away from zero, we cannot do so here.

occasioned by very poor years for the Central African Republic, Sierra Leone, and Zimbabwe, all relatively small African countries. As it is difficult for us to conclude that these years saw a dramatic decrease in world welfare because of a catastrophe in these countries, we see that these indices do not correspond to our intuition.

(4) Baseline Distributions

Figures 1 through 21 graph distributions of income for the world as well as for various countries, regions, and years. To have a visual anchor, each of the graphs contains two vertical lines corresponding to annual incomes of \$312 and \$554. The \$312 corresponds to one dollar a day in 2006.[14] The \$554 line corresponds to the poverty line referred to by the United Nations in the definition of the Millenium Development Goals. This line was originally defined by the World Bank as one dollar a day in 1985 prices. This corresponds to an annual income of \$554 in our data set.

Figure 1 plots the distribution of income for China in 1970. As mentioned in section 2, we break the Chinese income distributions into two: rural and urban. These two distributions and the integral of both (which corresponds to the total Chinese distribution) are depicted in Figure 1. We note that the total distribution is completely dominated by the rural distribution as rural population in 1970 was much larger than urban population. The smaller but richer urban citizens show up as a small "shoulder" to the right of the overall distribution. We note that the overwhelming majority of the rural (and therefore total) distribution lies to the left of the poverty line indicating an extremely poor society. The bulk of the urban distribution, on the other hand, lies to the right of the poverty line.

Figure 2 shows that corresponding distributions for 2006. We see that the relative size of the urban and rural distributions has converged, reflecting the massive migration of population to urban areas. But mass migration was not the only thing that went on in China during the last 36 years: the large growth rates of per capita income shifted the Chinese distribution to the right. Figure 2 shows that the overall distribution moved because urban growth, but also because of rural growth. We note that both the rural and urban distributions have shifted to the right so much that the area to the left of the \$1/day poverty line is almost insignificant.

Figure 3 displays the total Chinese distributions for 1970, 1980, 1990, 2000 and 2006. Not only we see how the distribution moves to the right decade after decade, but also that the

[14] \$365 in 2006 corresponds to \$312 in 2000, the base year used by PWT6.2 used in this paper.

upper side of the distribution shifts faster than the lower side, reflecting the well documented increases in within-China income inequality.

Figure 4 displays the total distribution as well as the rural and urban decomposition for 1970 India. The figure is quite different from that of China 1970. The rural population is also a lot larger than the urban in India, but the relative average income is not that different: the urban distribution lies almost entirely inside the rural distribution. We also note that the fraction of the total distribution that lies to the left of the poverty lines is a lot smaller than it was for China (so, in 1970, poverty rates in India were smaller than in China). Figure 5 displays the same breakdown for 2006. We see that the relative size of the urban and rural distributions is more or less the same (that is, the massive migration to urban areas that we observe in China is not as apparent for India). We also see that the distributions have shifted to the right so much that, although there is still a non-negligible fraction to the left of the poverty line, poverty rates have declined dramatically. Figure 6 displays the decadal distributions for India. Unlike China, there is no obvious increase (or decrease) in overall income inequality.

Figure 7 displays the distribution for the United States, the third largest country in the world with a 2006 population of approximately 300 million citizens. The axis for this distribution have been changed to accommodate the much richer U.S. Notice that the US distribution shifts to the right, decade after decade, and that the distance between rich and poor visually increases.

Figure 8 shows the decadal distributions for Indonesia. With a population of 244 million people, it is the fourth largest country in the world today. The interesting aspect of the Indonesian distribution is that, whereas the upper side of the distribution shifts to the right in every decade, the left side of the distribution does not seem to gain much in the 1990s. This is probably due to the East Asian crisis of 1997 and the political turbulence that followed.

Figure 9 displays the distributions for Brazil (population 190 million). It is interesting to note how wide the Brazilian distribution is. Figure 10 displays the 1970 distributions for Brazil and Indonesia, a country of similar size and similar level of development. We see that the Brazilian distribution is much wider and a little bit richer. The interesting dynamics for Brazil occur at the bottom of the income scale. In order to analyze these interesting dynamics, Figure 11 blows up that part of the distribution. We note that the bottom part of the distribution shifted rapidly between 1970 and 1980. Those were the golden days of rapid economic growth in Latin America and, with growth came a rapid reduction of poverty. Then came the “debt crisis” and the “lost decade”, and the distribution shifted sharply to the left, leading to an increase in poverty. The reforms of the 1990s led to some positive but small shift of the distribution to the right, and to a consequent small but positive reduction in poverty. The acceleration of growth during the

2000s brought another shift to the right and another reduction in Brazilian poverty. We should note, however, that the small gains of the last 16 years did not compensate the losses of the lost decade, as the 2006 distribution is now about where the 1980 was.

Figure 12 displays the decadal distributions for Bangladesh. We note a sizeable increase in population but not a sizeable decrease in the area below the poverty threshold.

Figure 13 and 14 analyze Nigeria, the most populous country in Sub-Saharan Africa with 144 million citizens in 2006. Overall, we see that that the upper part of the distribution shifts to the right, the bottom part of the distribution has shifted to the left between 1970 and 2006. If we look at the detail of this movement displayed in Figure 14, we see that there is movement of this part of the distribution to the left between 1970 and 1980, between 1980 and 1990 and between 1990 and 2000. Things, on the other hand, seem to have improved between 2000 and 2006, as the bottom of the distribution has experienced increases in income.

The most salient feature of the dynamics of the Japanese distribution (Figure 15) is the substantial reduction in overall inequality (notice that the left side of the distribution has moved to the right much faster than the right side).

The behavior of the Mexican distribution (Figure 16) resembles that of Brazil, whereas the right side of the distribution has improved continuously every decade, the bottom part has experienced more uneven success: the substantial gains obtained during the 1970s vanished during the lost decade of the 1980s. There was virtually no movement during the 1990s and, despite the improvement experienced during the 2000s, the distribution around the $1/day region, in 2006 still lies to the left of that of 1980.

Figure 17 describes the behavior of the USSR and the countries that were created when it collapsed. The distribution shifted to the right between 1970 and 1980. The rich and the poor gained just about the same. By 1990, there explosion in inequality was so large that, while the top part of the distribution moved to the right, the bottom sharply shifted to the left. The crisis experienced by most of FSU countries (especially the two largest ones, Russia and Ukraine) during the 1990s forced a downward shift in the entire distribution. The shift was so pronounced that $1/day poverty became significant for the first time (this poverty arose mainly in some Central Asian republics of the FSU, Tajikistan and Uzbekistan). The positive growth experienced during the 2000s has brought the distribution back to the right, although poverty has not yet been eliminated.

After we compute the (lognormal) distribution of income for each country and each year between 1970 and 2006, we integrate all the distributions to estimate the world distribution of income. Figure 18 shows the WDI for 1970. In order to get some perspective, we also display the distribution of individual countries, grouped into regions (East Asia (labeled EA), South Asia (SA), Sub-Saharan Africa (SSA), Latin America (Latam), the USSR and Former Soviet Union (FSU), Eastern Europe (EEU), High Income Non-OECD countries (HNOECD) and OECD countries). We still also report the one-dollar-a-day lines ($312 and $554 per year).

In 1970, the WDI was trimodal (Fig. 19). There was a mode between the two $1/day lines, corresponding to the mode of the East Asian distribution (which, in turn, corresponds to the mode of the Chinese distribution which, in turn, corresponds to the mode of the Chinese rural distribution). The second mode is at about $1,000 and corresponds to the mode of South Asia which, in turn is slightly to the right of the mode of India. Finally, there is a third mode at around $5,000, which is somewhere between the mode of the USSR and that of the OECD. Note that a substantial fraction of the distribution lies to the left of the poverty lines, and that substantial fractions of the East Asia, South Asian, and African distributions lie to the left of the poverty lines. In 1970, $1/day poverty was large.

By 2006 things have changed dramatically (Fig. 20). First, note that the three modes disappeared. Instead, we have one mega-mode at an annual income of around $3,300, which roughly corresponds to the mode of East Asia and South Asia. To the right of the mode there is quite a substantial "shoulder" marked by the roughly 1 billion rich citizens of the OECD. At the other extreme, there is a thick tail at the bottom of the distribution marked by Sub-Saharan Africa. The fraction of the overall distribution to the left of the poverty lines has been reduced dramatically relative to 1970. Interestingly, most of the distribution to the left of the poverty line in 2006 is from Africa.

Figure 21 puts together the world distributions for 1970, 1980, 1990, 2000 and 2006. We note that the middle mode starts to disappear by 1980 and is completely gone by 1990, whereas the rightmost mode starts to vanish in 1990 and it disappears in 2000.

It is interesting to see how the WDI estimated using lognormal distributions compares to the one we get using non-parametric kernels in Sala-i-Martin [2006]. The result for 2006 is reported in Figure 22. The two distributions are not identical but the overlap is striking. This suggests that, the worldwide distribution of income is not too sensitive to the exact methodology used to estimate individual country distributions. In the next sections we will see that the global estimates of poverty and inequality are not sensitive to this method either.

(5) Baseline Estimates of Poverty

Our discussion of world and regional poverty and inequality will center around the headcount ratio measure, which is the fraction of individuals earning a lower income than a given amount, the poverty line. While other measures of poverty exist (the poverty gap, and the Foster-Green-Thornbecke indicators), we find the headcount ratio the most intuitive, well-understood, and commonly used measure both in the literature on poverty and in debates concerning it; therefore, we focus on it. However, although the $1 a day poverty line in 1987 US dollars remains the official definition of poverty according to the World Bank,[15] any specific poverty line above the lowest income compatible with survival (below which, by definition, no individuals could subsist, rendering the poverty rate zero) is arbitrary. Therefore, we present estimates for poverty lines corresponding to $1, $2, $3, $5, $7.50 and $10 a day in the dollars of the WB poverty line, which in US 2000 dollars (the currency of the Penn World Tables) are $554, $1108, $1662, $2770, $4155 and $5540 a year. In addition, we consider a poverty line of $365 in 2006 US dollars, which amounts to $312 a year in the currency of the PWT. We consider such a multitude of poverty lines not only because of the arbitrariness of setting a single line, but also in order to provide a better picture of the evolution of income distributions in the lower tail.

Figures 23 and 24 and Table 1 present the evolution of poverty rates and poverty counts for a variety of poverty lines for the world as a whole from 1970 to 2006. Figure 23 confirms the findings of Chen-Ravallion (2004) and Sala-i-Martin (2002a and b, 2004, 2006) that the $1-day world poverty rate has fallen since 1970, and has been falling almost continuously throughout the period, with a particularly sharp decline in the late 1970s and early 1980s. The poverty rate decline then decelerates after 1988, and is slightly over 5% in 2006. Moreover, and in contrast to Chen-Ravallion (2004), Figure 24 shows that poverty rates have been falling not just for the $1-a-day line, but for all poverty lines considered. In fact, while the decline in the $1-a-day poverty rate slows down, the poverty rates corresponding to higher poverty lines decline increase the rate of their decline. One can see a “tsunami effect” as successive poverty rates remains stagnant for years or decades from the start of the sample period, and then begin falling rapidly one after another.

[15] The exact line is closer to $1.08 in 1987 US dollars. Ravallion et. al. (2008) is a paper that considers revising this line upwards.

Figures 25 and 26 and Table 2 show that not only are poverty rates falling, but so are poverty counts, despite the fact that population has been rising steadily throughout the sample period. The poverty counts for the $1, $2 and $3 poverty lines, as well as for the USD-2006 $1-a-day line have all fallen since 1970, and the counts for all the remaining lines peak during the sample period, and are currently on the decline. We learn that not only are poverty rates falling, but that they are falling faster than population is rising.

(6) Baseline Estimates of Inequality and Welfare Analysis

Figure 27 and Table 3 present the Gini coefficient for the world under the baseline specification for the period 1970-2006, together with the Atkinson inequality indices for a variety of risk aversion coefficients in the unit interval. We see that inequality has declined according to all the Atkinson measures, as well as according to the Gini. Moreover, the decline in inequality after 1980 has been nearly monotonic for all indices, with a small rise around 1989, the date at which data on the former Soviet republics becomes available. This monotonic decline should be contrasted with the much more erratic behavior of the inequality measures in the early to mid-1970s, which nevertheless also tend to see a decline in inequality. It is also useful to note that while inequality falls at a slower pace in the 1990s than in the 1980s, the pace of inequality reduction in the 1990s continues unabated in the 2000s, which indicates that the global growth observed in the 2000s has not been particularly unequally distributed. In agreement with Bhalla (2002) and Sala-i-Martin (2002a and b, 2006), we find the world following an inverted-U path, with the inequality peak apparently attained in the early to mid-1970s, and a decline in inequality thereafter.

While these observations are crucial in that they document the fact of inequality reduction and of its persistence into the 2000s, they do not reveal to us some fundamental characteristics of this reduction. Figure 28 presents baseline GE indices for the world, broken down into components representing inequality between nations (the GE index computed by treating all individuals in a country as receiving the mean income), and inequality within nations (a weighted average of country GE indices). We note that, like all the Atkinson indices, the GE indices all show a decline in inequality. We also see that this decline occurs exclusively due to a large fall in between-country inequality. Within-country inequality follows a U-curve, reaching a minimum in the mid-1980s and then rising above its early 1970s level; however, the rise in within-country inequality from minimum to maximum is usually less than half (and sometimes less than a third) of the fall in between-country inequality. We also see that throughout the entire length of the period, between-country inequality is by far the larger component of overall inequality, at least for the indices with α in the unit interval. Hence, we again confirm the conclusion of Sala-i-Martin (2006) that world inequality is, in a large part, between-country inequality. We see that, in fact, inequality grew within countries since the mid-1980s (although much of this growth took place in the late 1980s and early 1990s with the breakup of the USSR), however, this rise in inequality was not large in comparison with what was happening on the between-country level. This observation accounts at once for the widespread feeling that inequality has risen coupled with the greater national diversity of the middle class: while inequality rose between one's neighbors in the same country, large and populous nations (China and India) grew to have sizeable middle classes that more than replenished the increased polarization in wealthier nations.

Figure 29 displays the time series of the 75-25 and 90-10 [16]percentile ratios for the world as a whole. We again see that both ratios have peaked in the 1970s and vastly fallen since then. The 75-25 ratio has decreased by more than a factor of two; however, it has begun a shallow rise since approximately 1998, whereas the 90-10 ratio has fallen from over 40 to about 25, and has stagnated in the 2000s. While these recent trends appear potentially worrisome, they suggest that any recent rise in inequality may be between the lower and upper segments of the world middle class (the 75th and 25th percentiles), rather than the richest and poorest (90th and 10th percentiles).

We conclude our discussion of the baseline estimates by considering the impacts of growth and inequality on welfare. While inequality may be an important component of our assessment of a society, it is clearly not the only one; as we have seen, growth may be a much more important factor. In particular, even if inequality is considered to be unambiguously bad, a dramatic increase in GDP may offset the welfare loss of increasing inequality. It is therefore necessary to assess the world distribution of income not just

[16] These ratios are the ratios of the income of the person at the 75th percentile to the income of the person at the 25th percentile, and similarly for the 90-10 percentile ratio.

from the point of view of inequality reduction, but from the point of view of some notion of aggregate welfare, which allows us to perform a formal growth-inequality tradeoff. Figure 30 and Table 4 present the Atkinson and Sen welfare indices for the world, and shows that welfare has been increasing throughout our period of interest, with an acceleration towards the 2000s. All the welfare indicators more than doubled (and some indices almost tripled) since the 1970s. There is a slight slowdown in the growth of welfare around 1990, which can obviously be explained by the fall of the Soviet Union. Overall, welfare between 1970 and 2006 increased by 146% if we use the Sen index and by somewhere between 128% and 158% if we use the various Atkinson indexes.

(7) Regional Analysis

Figure 31 displays the evolution of GDP per capita for all the regions outside the OECD. As is well known, East Asia starts at that bottom of the world in 1970 and has experienced superlative growth rates over the last three decades. Starting at a similar position, South Asia has also experienced positive (but not as large) growth rates. Latin America grew during the 1970s, stagnated for about 15 years during the so called “lost decade” and has resumed its growth path over the last few years. The Soviet Union and Eastern Europe grew substantially before the fall of the Berlin Wall, then crashed spectacularly during the transition from communism, and have begun to recover during the last decade. The Middle East and North Africa grew during the 1970s, shrank between 1980 and 1990 and have been growing very slowly during the last few years. Africa has basically largely been stagnant with a small but negative decline in GDP per capita between 1970 and 1995 and a small but positive growth between 1995 and 2006. The world average, also shown in the picture (and which include the OECD) has grown substantially over the period.

What have these GDP per capita trends implied for the evolution of poverty at the regional level? The panels in Figure 32 and Tables 5 and 6 show the $1/day and the $2/day poverty rates and counts for each region. East Asia and South Asia start the period as some of the poorest of the developing regions and end it as having decreased poverty to the level of the more affluent countries in Latin America and the Middle East. As a result, East and South Asian $1-a-day poverty rates decline to less than 10%, whereas other rates decline by a factor of 3 or 2 (for the higher rates). Other regions have not fared as well. Latin America and the Middle East show progress in the reduction of poverty rates, but seem to stagnate with respect to poverty counts; poverty reduction there does not exceed the pace of population growth. Eastern Europe and the former USSR have very low poverty rates and counts initially, grow poorer during the transition from communism, but reverse this trend in favor of poverty reduction in the 2000s. Finally, Africa's poverty rates increased between 1970 and 1996. However, in 1996, the African $1-a-day (and to a lesser extent the $2-a-day) poverty rate begins to fall, reaching around 30% in 2006, having started from 40% in 1970.

This fall in poverty rates must be accounted by some combination of a rise in poor countries' growth rates and a fall in poor countries' inequality through redistribution from the rich to the poor, or through the poor growing faster than the rich. To assess the relation of growth and poverty reduction, Figure 33 presents a series of graphs plotting the $1/day poverty rate in each region considered (excluding the OECD) and the region's per capita GDP. It is immediately visible that the series are almost perfect mirror images of each other: the poverty rate falls when per capita GDP rises and vice versa.[17] In particular, one should note how the poverty rate series replicates the major changes in regional per capita GDP that characterize the past 30 years: notably, the sustained rise in GDP in East and South Asia, the crisis of the Soviet Union, and the stagnation of Africa followed by renaissance. In particular, we see no examples of poverty reduction without growth (or sustained rises with poverty accompanying growth) on a regional scale.

To see how inequality evolves at the regional level, figure 34 plots the Gini coefficient over time for each of the regions. The main message of this figure is that the Gini coefficients have remained largely constant. The main exception was the Soviet Union which experienced a surge in inequality from 0.25 to 0.50 during the first years of the transition from communism. It is interesting to see that inequality in East Asia has not increased substantially (in fact, it has decreased). This is due to the convergence of China to the rest of East Asian countries, which has reduced the across-country component of Asian inequality. In any event, the point is that the growth process experienced by each of the regions seem to dominate the dynamics of inequality when it comes to explain the

[17] The actual correlations of the series are approximately -0.8

evolution of poverty rates. In other words, inequality did not increase enough to offset growth in order to generate increasing poverty.

We conclude by considering welfare measures by region. Figure 35 presents two welfare indexes by region: the Sen index and Atkinson(1). The regional Atkinson welfare indices are the relative certainty equivalents of the income distribution *in that region*; hence, saying that the Atkinson welfare for South Asia is twice that for Africa (for example) implies that an imaginary immigrant would be willing to pay twice as much to be randomly assigned an income position in South Asia as to be randomly assigned an income position in Africa. We see East Asia, Latin America and the Middle East converging at the world average welfare level to form a "global middle class". We again see that East Asian growth clearly compensated for any rise in inequality, and East Asia appears to converge fully to the world in terms of welfare by 2006.

(8) Sensitivity Analysis

As discussed in Section 2, we analyze departures from the baseline specification in multiple directions. We first present a general analysis of sensitivity to all these variations in order to show the robustness of our results, and then assess the differences between different departures and their implications for what we may state about income distributions.

To review, the variations for sensitivity analysis are:

1) Functional form of the country distribution of income: lognormal, gamma, Weibull.

2) Interpolation / Extrapolation method: PCHIP / horizontal, linear, nearest-neighbor / hybrid.

3) Computation of parametric distribution parameters from Ginis rather than quintiles.

4) Survey misreporting correction using functional form.

5) Breaking up China and India into urban and rural components.

6) GDP: PWT 6.2, World Bank, Maddison, World Bank after PPP revision (last series is considered separately).

(a) Sensitivity Analysis against all variations

We first discuss sensitivity analysis for all variations taken together, and then discuss in greater detail some specific variations.

Figures 36 and 37 show the time series for the $1/day poverty rate and for the Gini coefficient under all the departures discussed. It is clear that both series decline over time, not only for each specification considered, but also overall; the lowest poverty rate (or Gini) for any specification in 1970 is higher than the highest poverty rate (Gini) for any specification in 2006. It is also clear that the greatest departures from the baseline occur if GDP is varied; in particular, the significantly higher Chinese GDP in 1970 according to Maddison's dataset significantly decreases the extent of poverty reduction that has occurred. The effects of alternative survey procedures, distributional assumptions, and the survey adjustment are smaller, and the effects of interpolation are negligible. Nevertheless, using gamma or Weibull distributions in place of the lognormal distribution implies a higher residual poverty rate when poverty reduction slows down in the 1990s; we will see later that these estimates are inferior to the baseline specification.

Figure 38 presents upper and lower bounds on the six poverty rates we have considered for the world, which show 1) that the general levels and trends of poverty according to all six lines are robust to alternative specifications, and 2) that the "tsunami effect" on poverty, expected if the major source of poverty reduction is East and South Asian growth, is also evident regardless of the methodological assumptions we employ.

The robustness of trends to sensitivity analysis holds not only for the poverty rate and the Gini, but for the vast majority of the series analyzed. Table 7 presents the correlation coefficients of adjustments along all levels analyzed to the corresponding baseline series for the major series we consider for the world as a whole.[18] We see that most series are very highly correlated ($\rho > 0.99$) with their baseline counterparts, and almost all series are highly correlated ($\rho > 0.9$) to the baseline. Therefore, the lessons

[18] We use the correlation coefficient as a descriptive statistic to capture common linear trends. Since we are not analyzing survey error, the correlation coefficients in this and subsequent tables should not be seen as objects of inference.

about worldwide trends – specifically, falling poverty and inequality for all or almost all indices – are robust to sensitivity analysis.

From the graphs in Figures 36 and 37, it appears that while all series follow the same trend as the baseline, some series are virtually identical to it. Table 8 presents for all series considered in Table 7 a quantitative measure of the extent to which the series are identical to the baseline. Notice that if two series y and y' are identical, then in a regression

$$y' = \alpha + \beta y + \varepsilon$$

we expect that $\alpha = 0$ and $\beta = 1$. We therefore measure the difference between the two series by a weighted sum of the widths of the confidence intervals of these parameters. Specifically, we test $\hat{\beta} - 1 = 0$ and compute the 95% confidence interval (c_{1L}, c_{1U}). We also test $(\hat{\alpha} / \overline{y}) + \hat{\beta} - 1 = 0$ since $\hat{\alpha} = \overline{y}' - \hat{\beta}\overline{y}$ and compute the confidence interval (c_{2L}, c_{2U}) for the linear combination on the left-hand side. We do the last procedure to see if the mean of the modification y' differs by a "significant" fraction from the mean of the baseline series y. Finally, we aggregate the two confidence intervals by taking the sum of the largest aggregate departures from the null that are consistent with the intervals: $G = \max(|c_{1L}|, |c_{1U}|) + \max(|c_{2L}|, |c_{2U}|)$

This statistic has no inferential content since we do not have a theory of the error term in the sensitivity analyses. Rather, it is meant as an upper bound for the departures of the modified series from the baseline in terms of both location and scale. We see in Table 8 that most series are not in fact identical to the baseline; however, we see that some series are much closer to it than others. First, we see that of all the variations, using Maddison GDP appears to produce the greatest and most frequent deviations from the baseline, most pronounced for the poverty series, which reinforces our observation that variations in country GDPs explain most of the changes in the world distribution of income. Second, we see that the optimal distribution modification produces series that are by far the closest to their baseline counterparts.

(b) Sensitivity to Functional Forms

In addition to the difficulties with assessing inequality indicators with indices outside the unit interval, the gamma and Weibull distributions fit the data noticeably worse than the lognormal distribution does. In Appendix B, Table 1, we present the percentages of the cumulative world population over the period 1970-2006 that is accounted for by countries with lognormal, gamma and Weibull distributions respectively. We present these percentages with and without using the survey adjustment for misreporting, as well as for the case in which scale parameters are computed from survey Ginis. In all cases, over 98% of the cumulative world population is accounted for by countries with lognormal distributions. As would be expected, the optimal distribution series is nearly identical to its corresponding lognormal series. Hence, we learn from our analysis that of the three two-parameter distributions that we consider, the lognormal is the superior distribution to use if only one functional form were retained.

It is important to ask whether the lognormal distribution provides reasonable fit to the data in an absolute sense, rather than relative to some alternatives. One of our sensitivity analyses is to compute the lognormal scale parameters from Gini coefficients rather than quintiles. If the true underlying country income distributions are lognormal, then the series computed from Ginis should be identical to the series computed from quintiles. Table 8 shows that while these series are not identical, most of the series of our primary concern – the middle poverty rates, and the inequality and welfare indices in the unit interval – are close to their baseline series in the sense described above. Hence, we can be reassured that the true distributions can be taken as lognormal.

(c) Sensitivity Analysis for Regional Results

Besides the general trends in poverty and inequality, we can confirm the robustness of our finer results to alternative specifications. Figure 39 plots the poverty rates in Asia, Africa and Latin America, to confirm our initial observation that poverty went from being an Asian phenomenon to an African one – poverty in East and South Asia declines precipitously in the 1980s, whereas the African poverty rate rises in this period, and only recently begins a shallow decline. We see that one estimate of East Asian poverty (the one in which Maddison's GDP numbers are used) gives a much lower level for the poverty rate than do all the others; this shows the influence of GDP on poverty reduction. Figure 40 confirms our understanding of the changes in world inequality. First, all the GE measures in the unit interval decline uniformly over the period 1970-2006 (which implies that all the Atkinsons in the unit interval decline uniformly as well). Second, most world inequality remains between-country inequality, and total inequality declines because of a fall in between-country inequality that compensates for a rise in within-country inequality.

(d) Sensitivity to Misreporting

A potential critique of the household surveys used is the presence of potential biases in the reporting of very high or very low incomes. Potential sources of these biases are 1) the unwillingness of high-income individuals to divulge their financial information, or official top-censoring of reported incomes, and 2) the difficulty of converting in-kind income of the poor (which may be a substantial share of their income) into equivalent monetary values. It is clear that the first bias serves to increase the reported share of the income going to poorer individuals in society, and hence, to decrease reported poverty and inequality. The direction of the second bias is ambiguous, as in-kind income could be either overvalued or undervalued by the survey designers.

Assuming that we know the parametric form of the distribution of income, it is easy to correct for biases of this type under the additional assumption that the survey ranks each individual into the appropriate quintile (the rich can be identified as rich even if their precise income is not revealed, whereas the poor can be identified as poor if the monetization mechanism for in-kind income is not too flawed), and that all incomes are reported correctly (up to scale) with the exception of some incomes in the top and bottom quintile. Then, it is easy to see that the ratio of the incomes of each of the middle quintiles to the sum of the incomes of the middle quintiles (hereafter the standardized middle income shares) is a statistic that does not depend on the misreported data from the extreme quintiles, and hence, is consistently estimated. Since we need to recover only one scale parameter, these two statistics (the third is a function of the other two) are more than enough to do so. We estimate the scale parameter of the distribution by the minimizer of the sum of squared differences between the population and sample standardized middle income shares. Since sample quintile shares are consistent estimators of their population equivalents, this is a consistent estimator of the true scale parameter (assuming the distributional assumption holds).[19]

Figure 41 presents the $1/day poverty rates and counts, as well as the Gini coefficient series for adjusted vs. unadjusted specifications, for the three parametric distributions under consideration. We observe that the adjustments do not differ very much from the unadjusted series[20], and the trends of the adjusted and unadjusted series are very close. This fact is confirmed by Table 7, which presents correlations between the baseline measures and their adjusted counterparts (for the lognormal specification), most of which are very close to unity. The similarity is closest for the lognormal series; the gaps between adjusted and unadjusted series for the gamma and Weibull distributions are substantially larger. The gaps also appear to increase towards the end of the sample period. The differences that do exist suggest the unadjusted data gives too *pessimistic* a picture of the world: poverty and inequality are lower in 2006 using the adjusted estimates by all measures, and their decline is steeper over time. Hence, if we are confident in the lognormal distributional assumption (which seems most plausible of the three distributional assumptions used), then we can conclude that the net effect of misreporting in the extreme quintile is practically small, and if it exists, indicates that the incomes of the poor are underestimated by conventional survey procedures.

(e) Purchasing Power Parity in the wake of ICP

Following the conclusion of the International Comparisons Project (ICP) in November 2007, the World Bank has changed its methodology with respect to calculating country GDPs at PPP. This change resulted, in among other consequences, lowering Chinese and Indian GDPs by 40% and 35% respectively, which was highlighted in the popular press on many occasions (*The Economist*: Nov. 29, 2007; Dec. 19, 2007). Several criticisms have been made of this finding; in particular, that it considers prices in urban China only. In comparing the original and revised World Bank series, we see that the effect of the revision was largely to multiply each country's GDP series by a time-

[19] We present the motivation for our distributional assumptions in the Introduction.
[20] This claim should be qualified for poverty in the 1990s, since although the difference between the two series is on the order of several percentage points, the fact that poverty in the 1990s is historically low makes this a large relative difference. However, this difference is insignificant for the claim that poverty fell during the sample period.

invariant constant, which is the expected effect of applying the PPP adjustments derived from the ICP to all years from 1980 to 2006,[21] which changes world inequality only by changing the starting positions of countries, but not of their growth paths. Hence, this revision only postpones convergence if convergence was going on in the original series, rather than contradicts it.[22] We nevertheless compare the poverty and inequality estimates arising from the new WB series to our baseline estimates, and reach a conclusion that while the levels of many series have changed dramatically, the trends change very little, and the lessons we learned from the PWT data continue to apply with our new results.

Figure 42a shows comparative plots of the $1/day world poverty rate for the baseline specification and the PPP revision. We see that while the level of poverty is higher with the revision, the revised series also shows sharply falling poverty. More importantly, the two series converge over time and become very close by 2006. This is easily understood; China has grown so much that by 2006 there are very few poor people in China with or without the revision, so the revision has a very slight impact on poverty in 2006. However, in 1970, China accounted for a large fraction of the world's poor, and had a high poverty rate; decreasing Chinese GDP in 1970 by virtue of the PPP revision has a large impact on the number of poor in China, and hence, in the world as a whole. We present China's poverty rate in the Figure 42b to verify our observation. In fact, with the PPP revision, poverty reduction is far more extensive than in the baseline case.

Figure 42c performs the same comparison for the Gini coefficients. Here, the levels are drastically different and do not converge: the Gini coefficient of the revised series in 2006 declines only to the level of the Gini coefficient of the baseline series in 1980. However, the revised series declines noticeably, so we continue to observe falling world inequality and hence, convergence across people even if we accept the revision.[23]

[21] Given the World Bank's methodology in the revision, we naturally extend this series to 1970 by applying the WB's growth rates in the original series to the new 1980 GDPs.

[22] Such a revision is liable to generate some extraordinary numbers – Chinese GDP in 1980 is implied to be $465 in 2000 US dollars ($525 in 2005 US dollars), and by applying the old WB growth rates, it is $308 in 1970, which may be below the lower limit of survival.

[23] A potential argument could be that the baseline (PWT 62) series is closest to the truth in the early part of the sample, when initial PPP studies on China were performed, whereas the revised series should apply only in the latest part of the sample. However, even then, we see that if world inequality started out at the baseline level and ended at the revised level, it must have fallen since 1970 (although by very little). The World Bank presents the revised series without using the old PPP adjustment procedure for the early part of the sample.

We conclude by considering the Atkinson welfare series in the unit interval in Figure 43: all of them rise monotonically during the sample period, and all of them accelerate towards the end. We summarize these data in Table 9, in which we present correlations and closeness measures for the PPP adjustment relative to the baseline. It is evident that the levels are drastically different. However, the correlations are strong (although weaker than in most of the rest of the data) – they are less than 0.9 only for the poverty counts and rates corresponding to high poverty lines, and for some inequality indices outside the unit interval. In particular, the correlations of the welfare indices to the baseline are all over 0.99

(f) Sensitivity of Welfare Measures

Tables 7 and 8 show, respectively, the correlations and the closeness of fit between modifications and baseline series of the welfare indices (Atkinson and Sen). We see that the welfare indices are some of the most robust series considered in terms of trends (all modifications of the Sen index have over 0.99 correlation with the baseline), and many of them, particularly the Sen and the Atkinsons with coefficient in the unit interval, are also very close to the baseline series in location and scale. While this is serious evidence for the robustness of our conclusion that world welfare rises, we can say more. First, we see that not only are the welfare indices robust, but they are also very tightly related to GDP. Table 10.1 shows the correlations between the PWT62 GDP series and all welfare indices constructed using this series. We see that these correlations are greater than 0.99 for all indices whose coefficient is in the unit interval. Hence, we have strong evidence that for all natural measures of welfare, the growth component rather than the inequality component has been the principal source of variation over the past 37 years. Second, we observe that the growth rate of the welfare indices actually increases (as does the growth rate of GDP) during several parts of the sample period, including the 2000s. Figure 44 shows the range of growth rates of welfare indices in the unit interval associated with the PWT 62 GDP series, and we see several pronounced growth accelerations, in particular from 1990 to 1996 and from 2000 to the end of the sample period. Hence, we are justified in asserting that welfare not only rose during the sample period, but that it did so at an increasing rate of growth. Moreover, we observe that not only the levels, but the growth rates of welfare and GDP are correlated. Table

10.2 shows that the growth rates of the various welfare indices are tightly or moderately correlated with the growth rate of GDP. While this correlation falls off as the coefficient of the index (implied risk aversion of the observer) increases, we see that even for the unit coefficient, the correlation is high at around 0.7. This observation suggests that a large fraction of the variation in welfare growth is "explained" by GDP growth; the evolution of inequality is observed to have little effect not only on the levels of GDP but also on its growth rate. Finally, welfare has not only grown, but grown very significantly; Table 11.1 shows, world welfare by any measure has grown by no less than 77%, by most measures over 120%, and by some measures by 160%!

Since we have observed within-country inequality to have increased, it is of interest to consider changes in country-level welfare indices. Whether the aggregate or country-level indices are relevant depends on one's opinion of the scope of the moral community (whether it is global or national), and on one's concern with respect to inequality (envy or possibility of political disruption). Averaging the country-level welfare indices could be justified by construing the lottery behind the veil of ignorance as consisting of two parts: first, the individual is assigned to a country at random, and then, he is given an income level from the selected country's distribution. We consider the 187 countries present in 2006, and ask how many of these countries (and what size their total population) experienced rises in Atkinson and Sen welfare measures. We find that welfare unambiguously improved (considering all risk aversion parameters in the unit interval) in over 68% of countries, containing over 87% of the world's 2006 population. Welfare unambiguously deteriorated in 23 countries, totaling less than 5% of the world's 2006 population. We present a list of the latter in Appendix B, Table 2. Countries for which aggregate welfare fell are either ex-Soviet republics mostly in Central Asia, or African and Asian countries that had experienced protracted wars or periods of dictatorial rule during the period. Hence, aggregate welfare has risen for an overwhelming percentage of political units and people. Moreover, the extent of welfare growth in a given country, on average, has been likewise very high; Table 11.2 shows that the welfare of a country increased on average by about 110% over the 36 years of the sample period if one uses PWT 62 or WB series for GDP, by about 100% if one uses the PPP-revised series for GDP, and by 64% if one uses the Maddison GDP series.[24] Variations other than GDP appear to be of comparatively small significance.

Since these are welfare growth measurements, and take distributional changes into account, we are now free to conclude that, at least in terms of income, the world has experienced significant and relatively evenly distributed growth both from a global perspective and within most countries. Even taking distributional considerations into account, the past forty years have witnessed no less than a doubling of welfare.

(9) Conclusion

The main empirical results of this paper are: 1) Global poverty rates decline between 1970 and 2006. This is true for poverty lines ranging from \$1/day to \$10/day. 2) Global poverty counts decline between 1970 and 2006 for poverty lines from \$1/day to \$3/day. The total number of poor people has declined by more than 617 million if we use the \$1/day line and by more than 780 million if we use the \$2/day line. For higher poverty lines, poverty counts increased during the early years but are all declining by 2006. 3) Global income inequality has fallen between 1970 and 2006. This is true for the Gini coefficient, for a wide variety of Atkinson indexes and General Entropy indexes as well as the 90^{th}-to-10^{th} and the 75^{th}-to-25^{th} percentile ratios. 4) We systematically analyze the normative effects of changes in the world distribution of income using a strongly microfounded definition of welfare as the certainty equivalent of a lottery over all incomes in the world. We find that world welfare increases at increasing rates during our sample period, and records dramatic increases whether computed across citizens or across countries, notwithstanding increases in unweighted between-country inequality. Total growth in world welfare measured is estimated to be between 77% and 160%, with most estimates over 100%. 5) At the regional level we observe that poverty rates and GDP per capita behave as "mirror images" of one another: whenever GDP grows, poverty tends to decline and whenever poverty declines, GDP tends not grow. 6) Poverty has declined substantially in East and South Asia, and has recently began declining in Africa.

[24] Since we are considering growth numbers rather than levels, this does *not* indicate that Maddison estimates GDP to be 2/3 lower than the PPP-revised series; it is the latter series that reports the lowest GDP estimates we consider.

We show that our conclusions are robust to a general sensitivity analysis, and in particular, to three key areas of uncertainty: 1) uncertainty over the functional form of the country income distribution, 2) uncertainty over potential nonresponse biases in household surveys, and 3) uncertainty over the correct method of computing a PPP-adjusted GDP series. We show that the robustness extends not only to the global trends of falling poverty and inequality, but also that finer trends persist under specification changes. In particular we robustly demonstrate that, 1) poverty exhibits a "tsunami" effect, in which poverty declines decelerate for lower poverty lines and accelerate at higher ones, 2) poverty becomes an essentially African phenomenon, and 3) most of the decline in inequality is a decline in population-weighted between-country inequality.

Our data allows us to give a progress report on the first Millennium Development Goal of halving poverty from 1990 to 2015. Table 12 shows that estimates from our modifications in the sensitivity analysis indicate that so far, poverty has fallen by about 30% in the 16 years since 1990, giving the world ample time to reduce poverty by a further 20% of 1990 levels. If we accept the World Bank's recent PPP revision, then poverty has fallen by about 58%, and the first MDG has been achieved, since the PPP revision assigns to the 1990s a large part of China's poverty decline that the Penn World Tables and Maddison assign to the 1980s. Importantly, a large part of the decline in poverty has taken place in Africa. Using the Penn World Tables as our source of GDP, we see that Africa has decreased poverty by 20-25% from 1990 levels, making it likely that it will come close to, or perhaps even achieve the MDG within its continent.

Appendix: Proofs and Tables

Appendix A: Proof of Instability of Inequality Indices outside the Unit Interval

Proposition: Suppose that X is a nonnegative random variable, and we know its distribution F on the interval $[a,M]$. Then, 1) there exist nontrivial upper and lower bounds for $\text{GE}(\alpha)$ and $A(\gamma)$ for X if $\alpha \in (0,1)$ or $\gamma \in (0,1)$, and 2) there exist no such nontrivial bounds otherwise.

Proof: Without loss of generality, we consider only the GE index, where $\text{GE}(\alpha) = \frac{1}{\alpha(1-\alpha)}\left[1 - \frac{\int x^{\alpha} dF}{\mu^{\alpha}}\right]$ and $\mu = E(X)$

Note that if $\alpha \in (0,1)$, then x^{α} is concave, so $\int x^{\alpha} dF < \mu^{\alpha}$, and $F \in \arg\max_{F} GE(\alpha) \Leftrightarrow F \in \arg\min_{F} \int x^{\alpha} dF$.

If $\alpha \notin (0,1)$, then x^{α} is convex, so $\int x^{\alpha} dF > \mu^{\alpha}$, and $F \in \arg\max_{F} GE(\alpha) \Leftrightarrow F \in \arg\max_{F} \int x^{\alpha} dF$.

Suppose we know F on $[a,M]$, so $F\,|_{[a,M]} = \hat{F}$ for a given $\hat{F}$. We are also given that $\int x dF = \mu$, with μ given.

Then, $\int x^{\alpha} dF \geq \int_a^M x^{\alpha} d\hat{F}$, so for $\alpha \in (0,1)$, $GE(\alpha) \leq \frac{1}{\alpha(1-\alpha)}\left[1 - \frac{\int_a^M x^{\alpha} d\hat{F}}{\mu^{\alpha}}\right]$,

and $\text{GE}(\alpha)$ is bounded above for any a and M.

However, suppose $\alpha > 1$ and set $a = 0$ for convenience. Define ε as $\int_0^M d\hat{F} = 1 - \varepsilon$, so for any F consistent with $F\,|_{[0,M]} = \hat{F}$, it must be the case that $\int_M^{\infty} dF = \varepsilon$. Moreover, since $\int x dF = \mu$, it must be the case that

Suppose $\int_0^M dF = 1 - \varepsilon, \int x dF = \mu$. Then, consider distributing the remaining mass ε on the set $\{M, Z\}$, where $Z > M$. Let P_M be the fraction of the mass ε assigned to point M, and $P_Z = 1 - P_M$, so that P_M of the measure ε remaining people have income M, and the remaining people have income Z.

This is equivalent to considering F_Z, where $F_Z(x) = \hat{F}(x)(x \leq M) + \hat{F}(M)(x \in (M,Z)) + (x \geq Z)$

Since $\hat{\mu} := \frac{1}{\varepsilon}\int_M^{\infty} x dF = \frac{1}{\varepsilon}\left(\mu - \int_0^M x d\hat{F}\right)$ is known, we can write that

$\hat{\mu} = \int_M^{\infty} x dF = (MP_M + Z(1-P_M)) \Rightarrow P_M(Z) = \frac{Z - \hat{\mu}}{Z - M}$, so given $\hat{F}$ and M, P_M is a function of Z alone

Then, $\int x^{\alpha} dF_Z = \int_0^M x^{\alpha} d\hat{F} + \varepsilon\left[M^{\alpha}\frac{Z - \hat{\mu}}{Z - M} + Z^{\alpha}\left(\frac{\hat{\mu} - M}{Z - M}\right)\right]$, and since $\alpha > 1$, we have

that $\lim_{Z\to\infty} Z^{\alpha}\left(\frac{\hat{\mu} - M}{Z - M}\right) = (\hat{\mu} - M)\lim_{Z\to\infty} Z^{\alpha-1} = \infty$, so $\lim_{Z\to\infty}\int x^{\alpha} dF_Z = \infty$, and $\text{GE}(\alpha)$ is not bounded above.

Suppose instead that $\alpha < 0$, and set $M = \infty$ for convenience. Then, consider $F^* = \varepsilon + \hat{F}(x)(x \geq a)$, so $F(0) = \varepsilon$, and there is positive probability that individuals have zero income. Then, $\int x^{\alpha} dF^* = \infty$, so the $\text{GE}(\alpha)$ index is not bounded above.

Appendix B: Some Tables

Appendix Table 1: Optimal Distributions (Population Weighted)

Optimal Distr.	Freq.	Percent	Cum.
lognormal	6,405.5102	98.55	98.55
gamma	50.3753291	0.78	99.32
weibull	44.1144579	0.68	100.00
Total	6,500	100.00	

Optimal Distr., Adjusted	Freq.	Percent	Cum.
lognormal	6,405.8457	98.55	98.55
gamma	78.4110287	1.21	99.76
weibull	15.743234	0.24	100.00
Total	6,500	100.00	

Optimal Distr., Ginis	Freq.	Percent	Cum.
lognormal	6,405.5102	98.55	98.55
gamma	50.3753291	0.78	99.32
weibull	44.1144579	0.68	100.00
Total	6,500	100.00	

Appendix Table 2: Countries for which welfare unambiguously fell:

Angola	Burundi	Central African Republic
Gabon	Madagascar	Niger
Nicaragua	Togo	Congo, Dem. Rep.
Zambia	Zimbabwe	Sierra Leone
Liberia	Iraq	Kuwait
Qatar	Kiribati	Brunei
Somalia	Afghanistan	Tajikistan
Turkmenistan	Ukraine	

Appendix C: Consumption Adjustment

To adjust consumption surveys in order to use them in our analysis, we adapt the procedure of Bhalla (2002). We select all country-years for which both income and consumption surveys are available, and manually select which income and consumption surveys of those available for a given country-year to use. We base our selection on 1) similarity of source, and 2) similarity of income sharing units, units of analysis and equivalence scales. Altogether, we have 100 pairs of income and consumption surveys.

We then estimate the system of seemingly unrelated equations:

$$q_{ijI} = \beta_j q_{ijC} + u_{ij}, J = 1, \ldots 5$$

where *q* is the quintile share, *I* and *C* index income and consumption, *i* indexes observations (country-years), and we allow the u_{ij}'s to be correlated across *j* (since quintile shares must sum to unity, the errors in the above regression are probably correlated across quintile shares). We exclude a constant from estimation. Our estimates are as follows:

```
Seemingly unrelated regression
----------------------------------------------------------------------
Equation          Obs  Parms        RMSE    "R-sq"       chi2        P
----------------------------------------------------------------------
q1_I              100      1    1.785765    0.8624    1498.20   0.0000
q2_I              100      1    2.237161    0.9321    3755.21   0.0000
q3_I              100      1    2.337126    0.9662    7431.34   0.0000
q4_I              100      1    2.709944    0.9812    9206.86   0.0000
q5_I              100      1    8.073047    0.9801   10443.53   0.0000
----------------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
q1_I         |
        q1_C |   .8273436   .0213748    38.71   0.000     .7854498    .8692374
-------------+----------------------------------------------------------------
q2_I         |
        q2_C |   .8973646   .0146437    61.28   0.000     .8686634    .9260658
-------------+----------------------------------------------------------------
q3_I         |
        q3_C |   .9321035   .0108126    86.21   0.000     .9109111    .9532958
-------------+----------------------------------------------------------------
q4_I         |
        q4_C |   .9756106   .0101677    95.95   0.000     .9556824    .9955388
-------------+----------------------------------------------------------------
q5_I         |
        q5_C |   1.072232   .0104922   102.19   0.000     1.051668    1.092797
------------------------------------------------------------------------------

Correlation matrix of residuals:

         q1_I     q2_I     q3_I     q4_I     q5_I
q1_I   1.0000
q2_I   0.9217   1.0000
q3_I   0.7526   0.9033   1.0000
q4_I   0.3906   0.5839   0.7973   1.0000
q5_I  -0.7649  -0.8790  -0.9198  -0.7769   1.0000

Breusch-Pagan test of independence: chi2(10) =   616.843, Pr = 0.0000
```

Hence we see that the residuals are highly correlated across *j*, so the SUR procedure made sense.

We then multiply all consumption quintile shares for surveys in the WIDER-DS dataset that we use by these estimates, and renormalize the resulting shares to sum to unity. (In practice, the shares sum very close to unity even without renormalization).

Below is the list of countries and regions affected by this (Income indicates number of income surveys, and Cons. indicates number of consumption surveys).

	ccode	cname	country	group	region	Income	Cons.
5.	5	Burundi	BDI	1	ssa	0	2
13.	13	Botswana	BWA	1	ssa	1	1
18.	19	Cote d'Ivoire	CIV	1	ssa	1	8
19.	20	Cameroon	CMR	1	ssa	1	1
28.	29	Egypt, Arab Rep.	EGY	1	mena	0	4
30.	31	Ethiopia	ETH	1	ssa	0	4
36.	37	Ghana	GHA	1	ssa	0	7
37.	38	Guinea	GIN	1	ssa	0	2
38.	39	Gambia, The	GMB	1	ssa	2	2
39.	40	Guinea-Bissau	GNB	1	ssa	0	2
46.	47	Indonesia	IDN	1	ea	0	9
48.	50	Iran, Islamic Rep.	IRN	1	mena	0	7
52.	54	Jamaica	JAM	1	la	0	11
53.	55	Jordan	JOR	1	mena	0	4
55.	57	Kenya	KEN	1	ssa	3	2
60.	62	Morocco	MAR	1	mena	1	4
61.	63	Madagascar	MDG	1	ssa	0	5
63.	65	Mali	MLI	1	ssa	0	2
64.	66	Mozambique	MOZ	2	ssa	0	1
65.	67	Mauritania	MRT	1	ssa	0	7
67.	69	Malawi	MWI	1	ssa	4	1
69.	71	Namibia	NAM	2	ssa	0	1
70.	72	Niger	NER	1	ssa	1	3
77.	79	Pakistan	PAK	1	sa	0	12
81.	83	Papua New Guinea	PNG	2	ea	0	1
85.	87	Rwanda	RWA	1	ssa	0	2
86.	88	Senegal	SEN	1	ssa	1	2
95.	97	Tunisia	TUN	1	ssa	1	3
98.	100	Tanzania	TZA	1	ssa	1	4
103.	105	South Africa	ZAF	1	ssa	2	2
106.	108	Zimbabwe	ZWE	1	ssa	1	2
116.	118	Sierra Leone	SLE	1	ssa	1	1
123.	125	Algeria	DZA	1	mena	0	2
127.	129	Cambodia	KHM	1	ea	0	3
145.	147	Laos	LAO	1	ea	0	2
149.	151	Mongolia	MNG	1	ea	0	2
157.	159	Djibouti	DJI	2	mena	0	1
160.	162	Yemen	YEM	1	mena	0	2
161.	163	Vietnam	VNM	1	ea	0	3
164.	166	Bosnia and Herzegovina	BIH	2	eeu	0	1
165.	167	Croatia	HRV	1	eeu	0	2
168.	170	Albania	ALB	1	eeu	0	2
184.	186	Tajikistan	TJK	1	exsoviet	0	2
192.	194	India, Urban	INU	1	sa	0	12
193.	195	India, Rural	INR	1	sa	0	12

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Figure 1: China in 1970

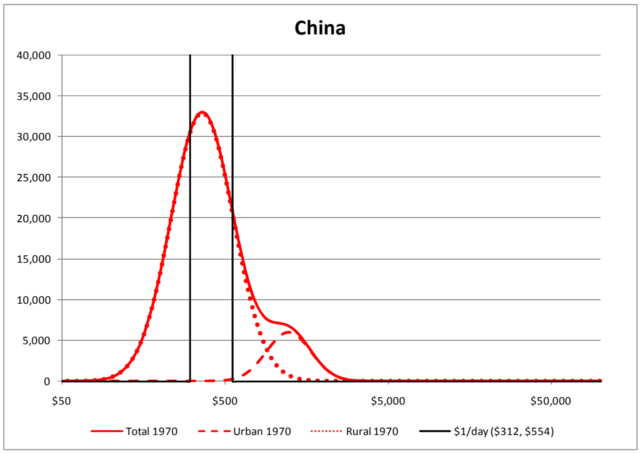


Figure 2: China in 2006

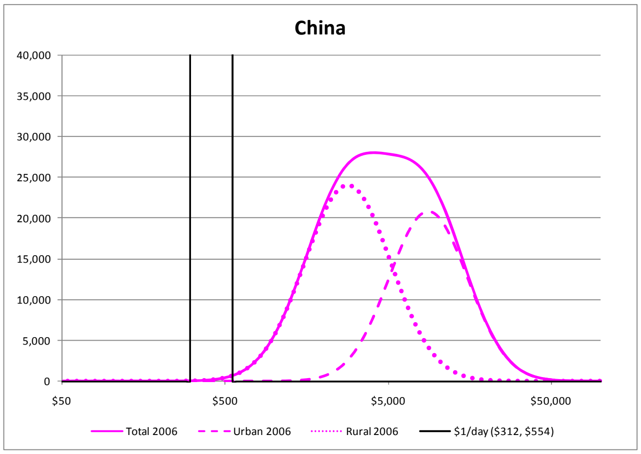


Figure 3: Chinese Income Distribution 1970-2006

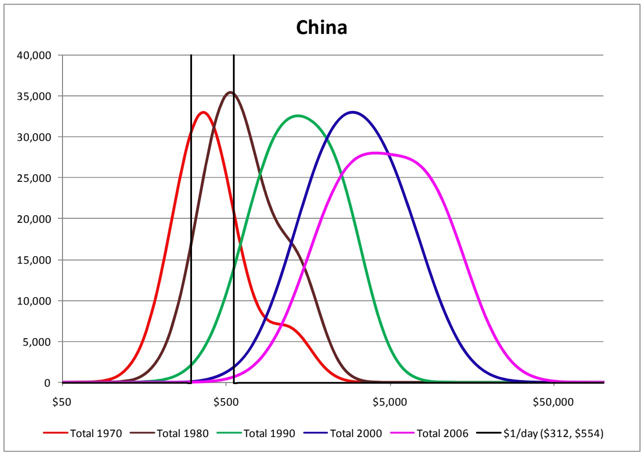


Figure 4: India in 1970

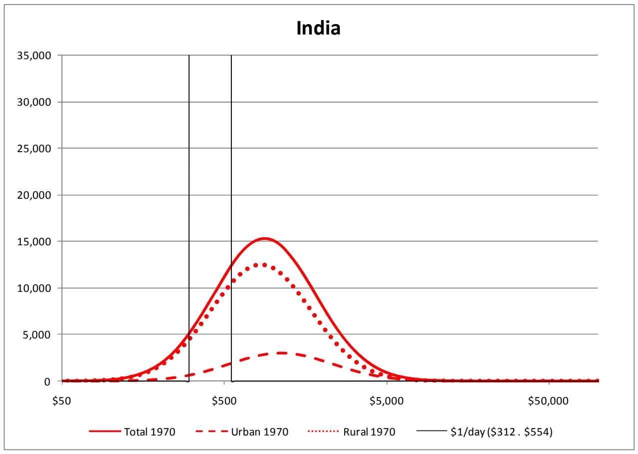


Figure 5: India in 2006

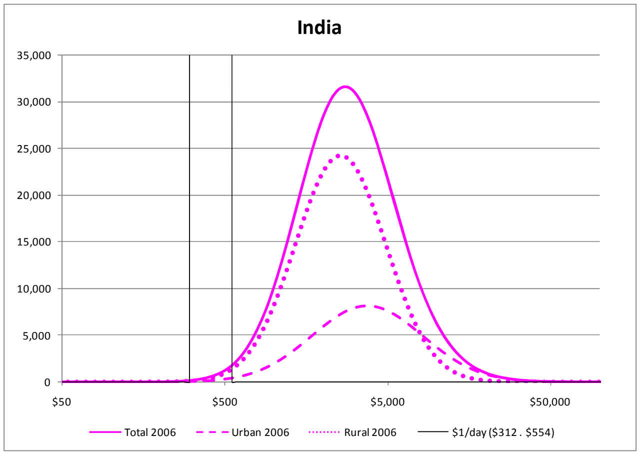


Figure 6: India 1970-2006

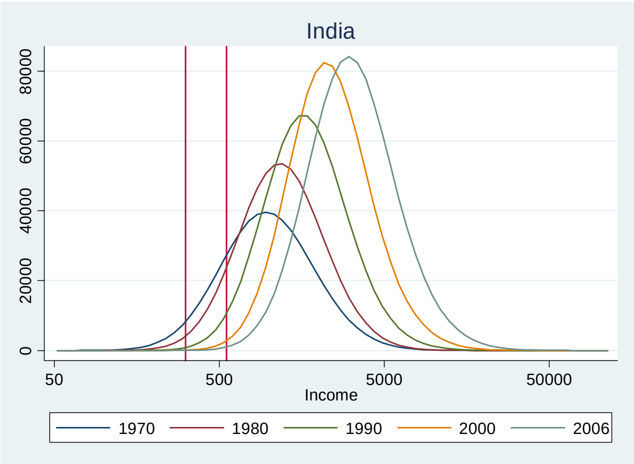


Figure 7: United States 1970-2006

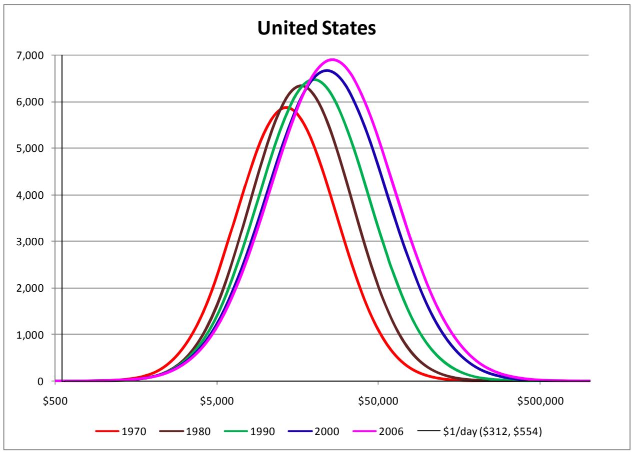


Figure 8: Indonesia 1970-2006

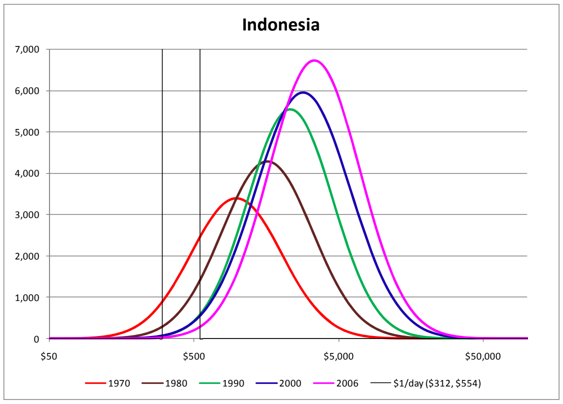


Figure 9: Brazil, 1970-2006

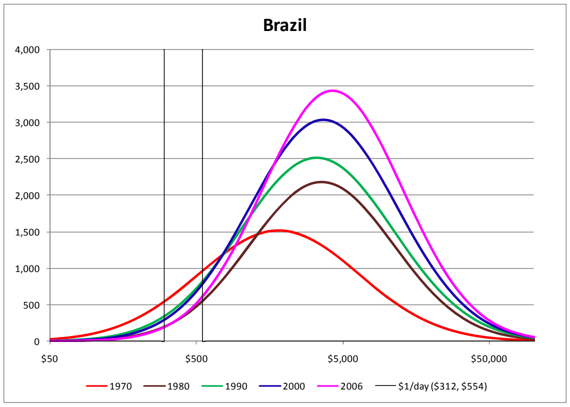


Figure 10: Brazil vs. Indonesia

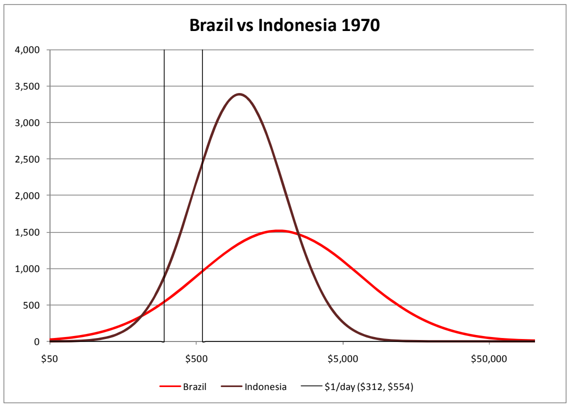


Figure 11: Poverty Dynamics in Brazil 1970-2006

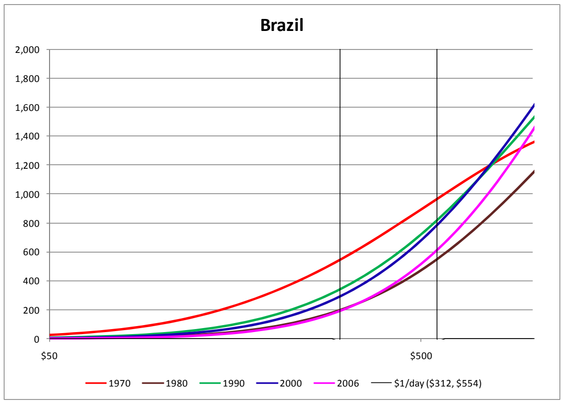


Figure 12: Bangladesh 1970-2006

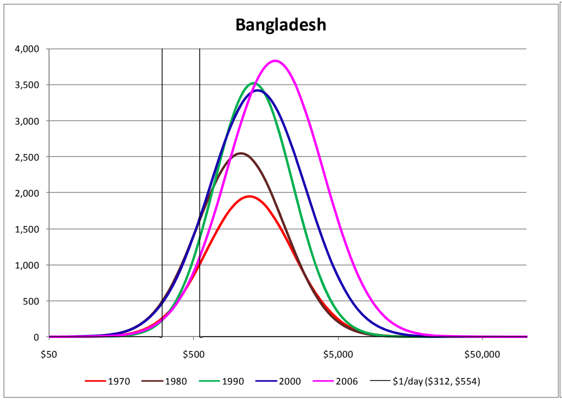


Figure 13: Nigerian Income Distribution 1970-2006

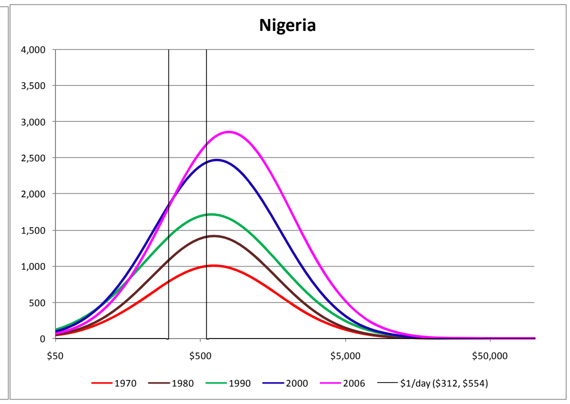


Figure 14: Poverty Dynamics in Nigeria 1970-2006

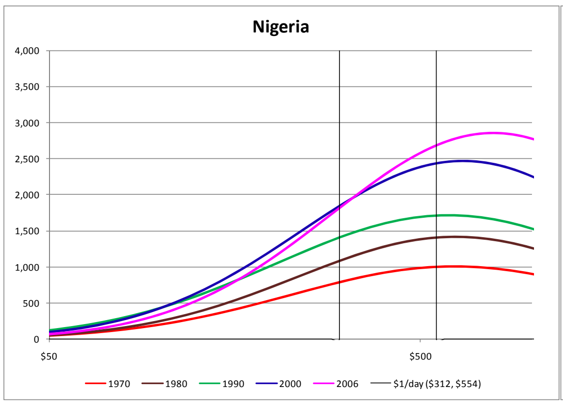


Figure 15: Japan 1970-2006

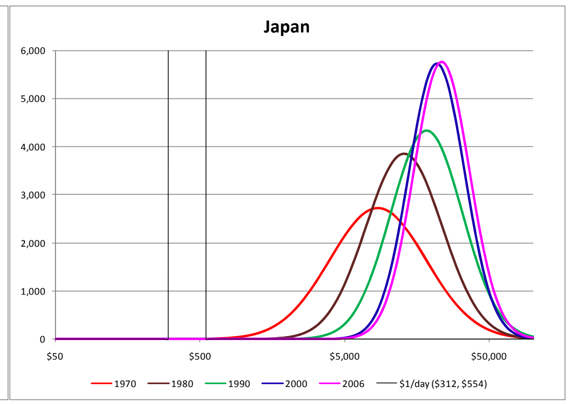


Figure 16: Mexico 1970-2006

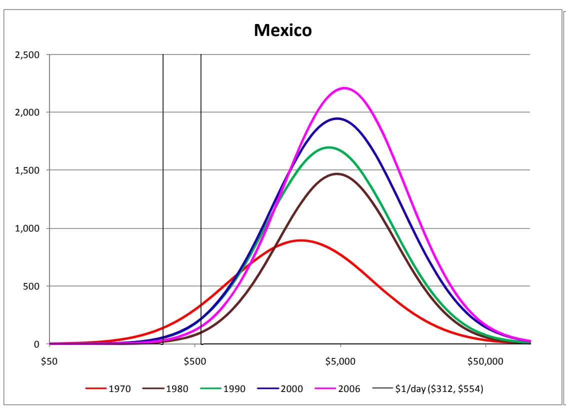


Figure 18: The (Former) Soviet Union 1970-2006

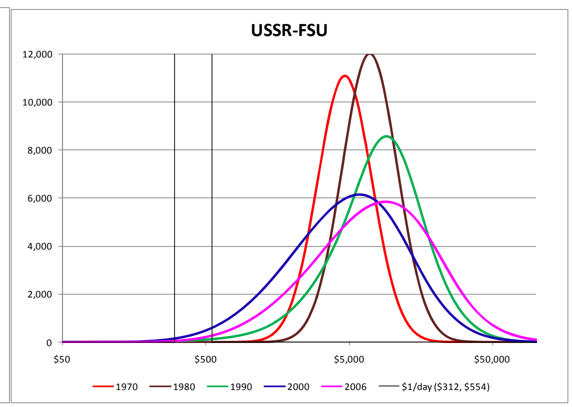


Figure 19: World Distribution of Income by Region, 1970

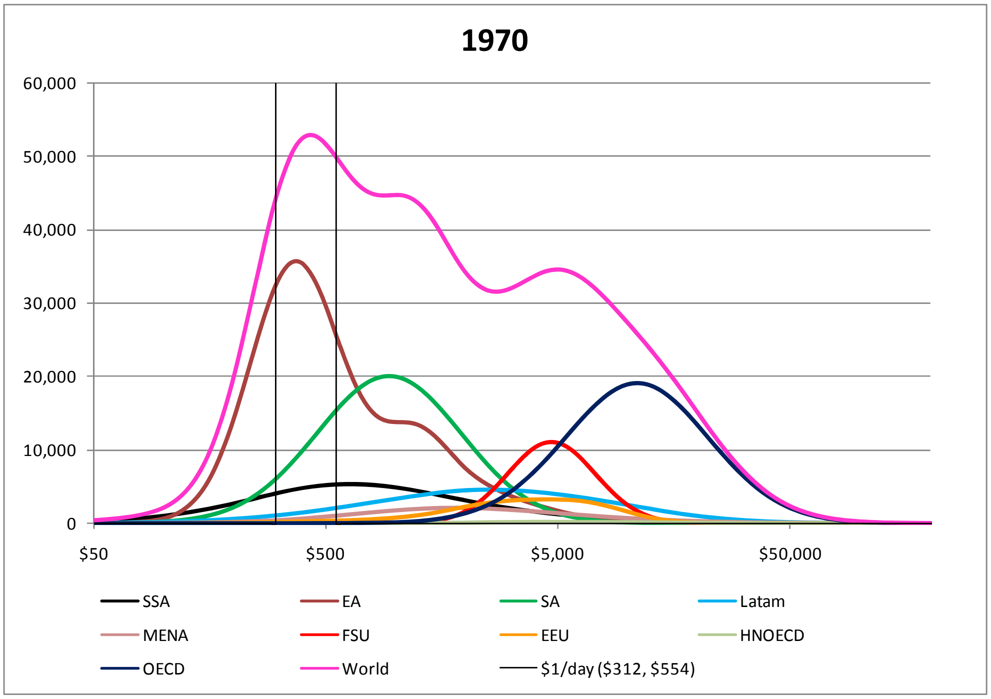


Figure 20: World Distribution of Income by Region, 2006

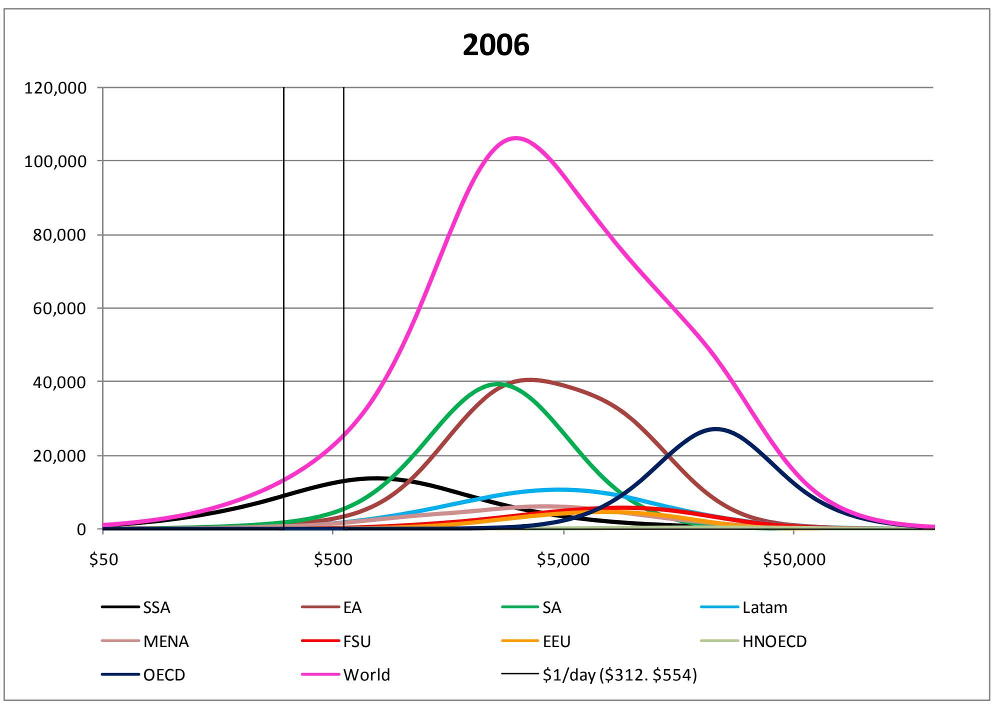


Figure 21: World Distribution of Income, 1970-2006

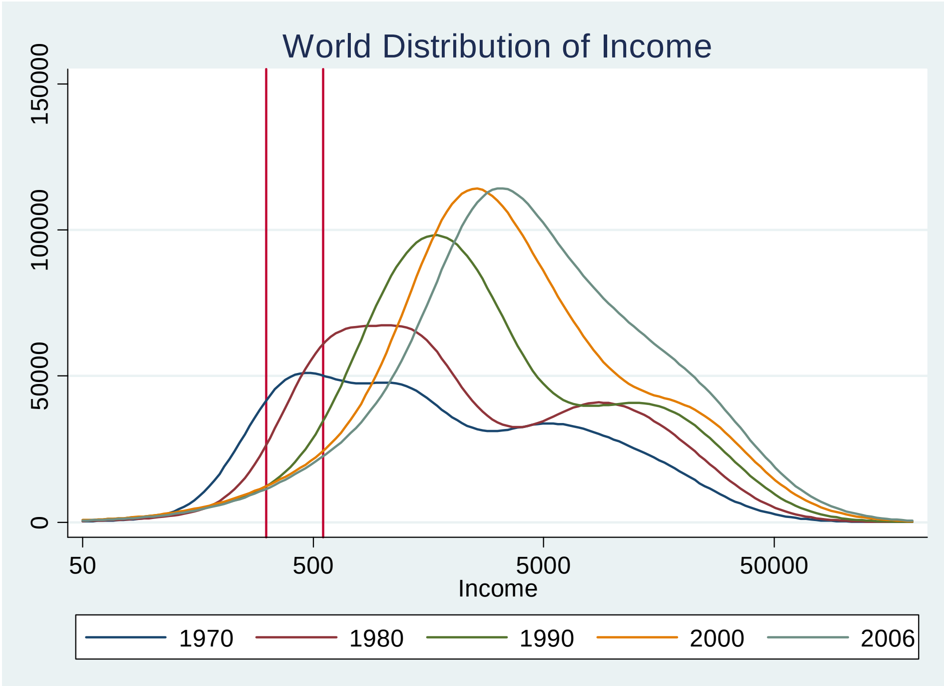


Figure 22: Comparison of Normals and Kernels

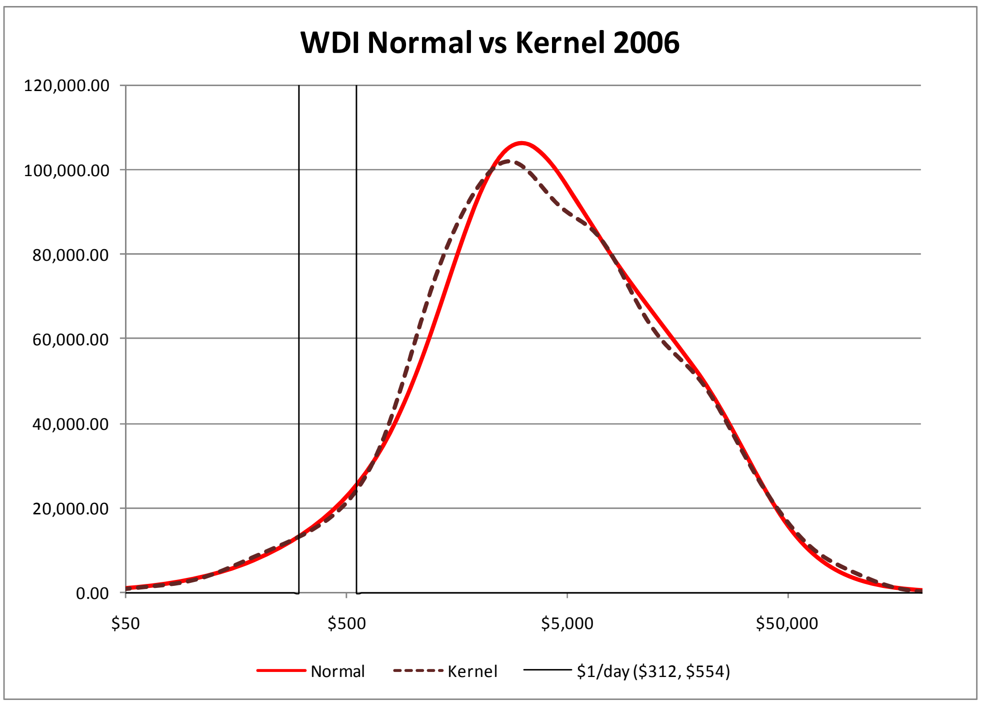


Figure 23: World $1/day Poverty Rate, Baseline

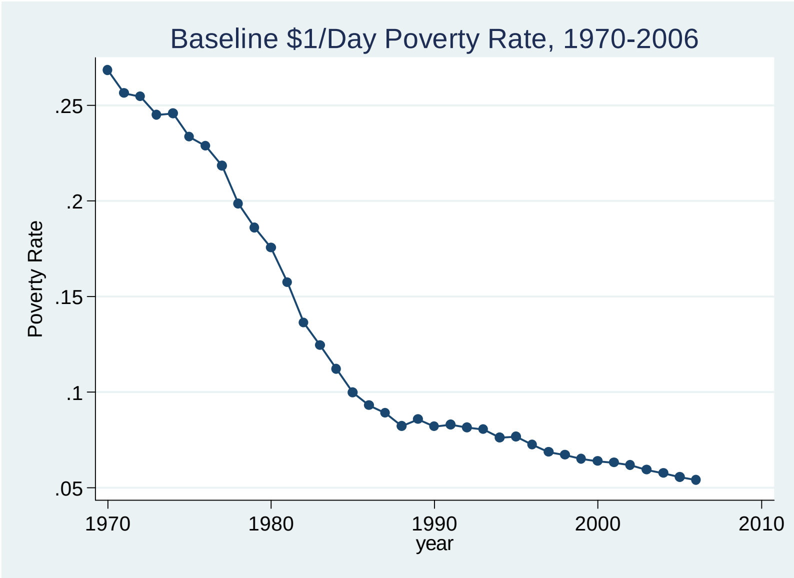


Figure 24: World Poverty Rates, Baseline

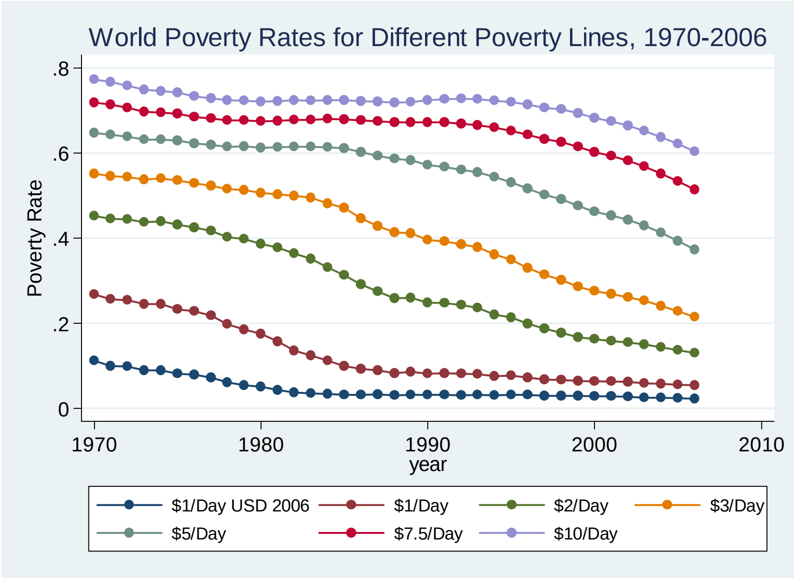


Figure 25: World $1/day Poverty Count, Baseline

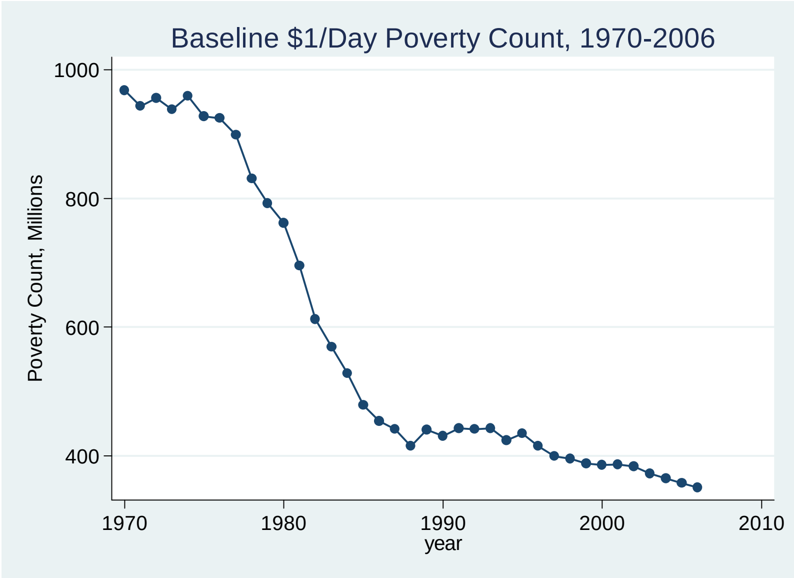


Figure 26: World Poverty Counts, Baseline

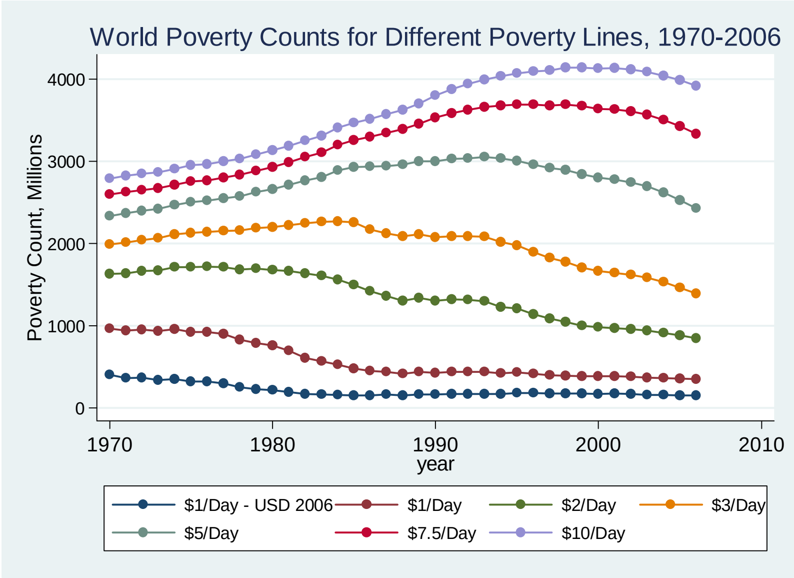


Figure 27: World Inequality Profile (Gini and Atikinson), Baseline:

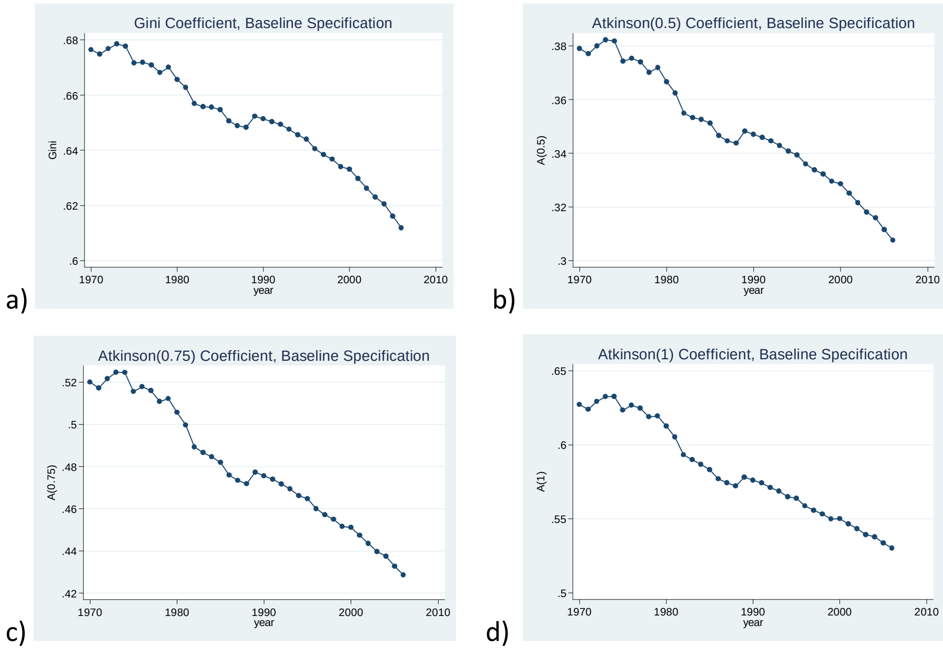


Figure 28: World Inequality, Within and Between Countries, Baseline

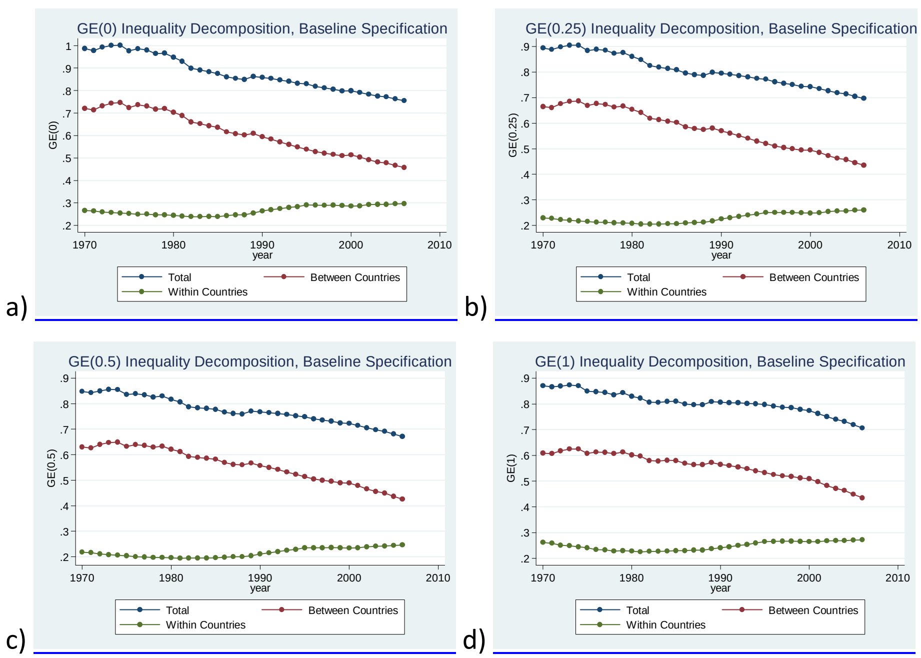


Figure 29: World Percentile Ratios, Baseline Specification

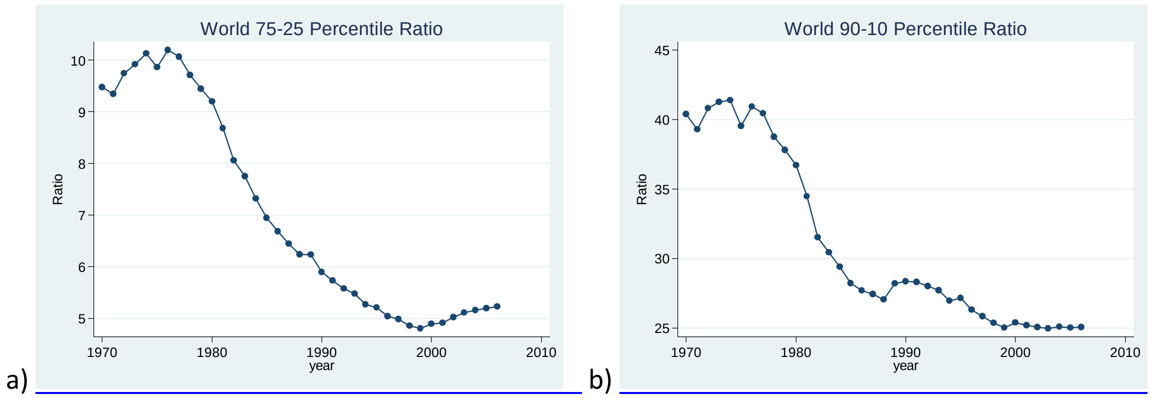


Figure 30: World Welfare, Baseline

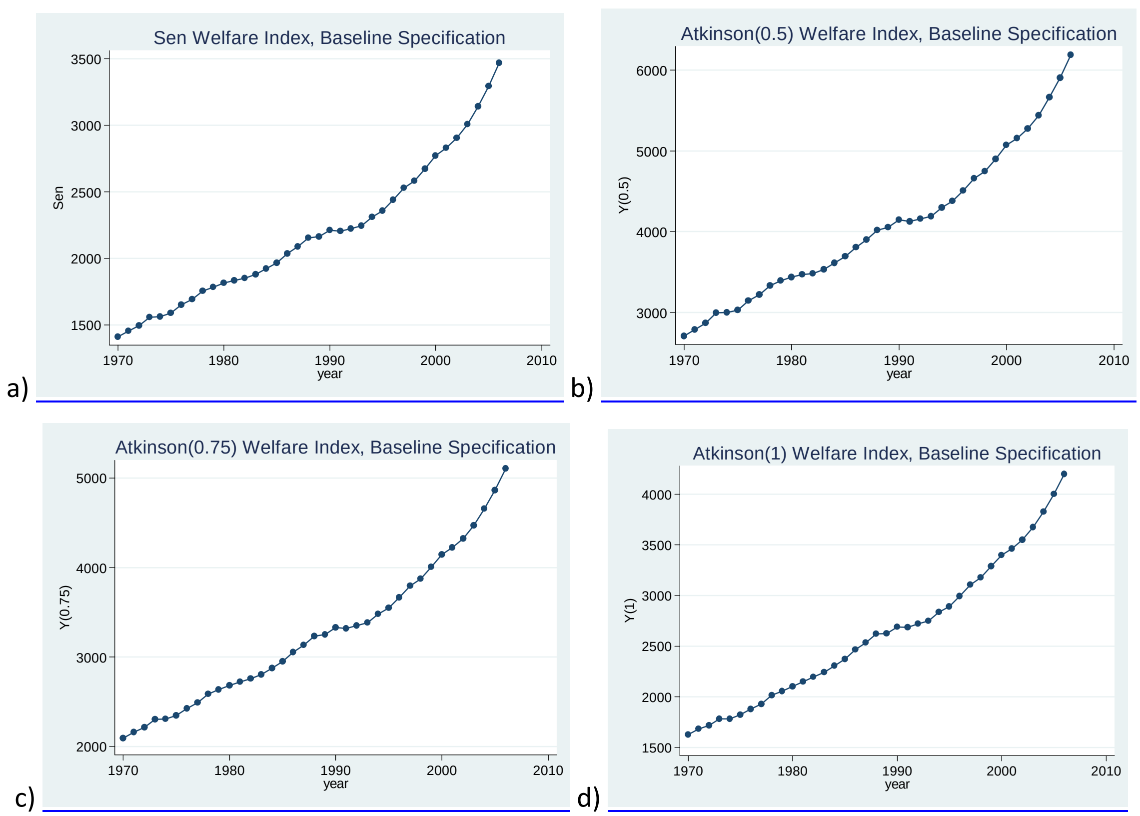


Figure 31: GDP per capita by Region

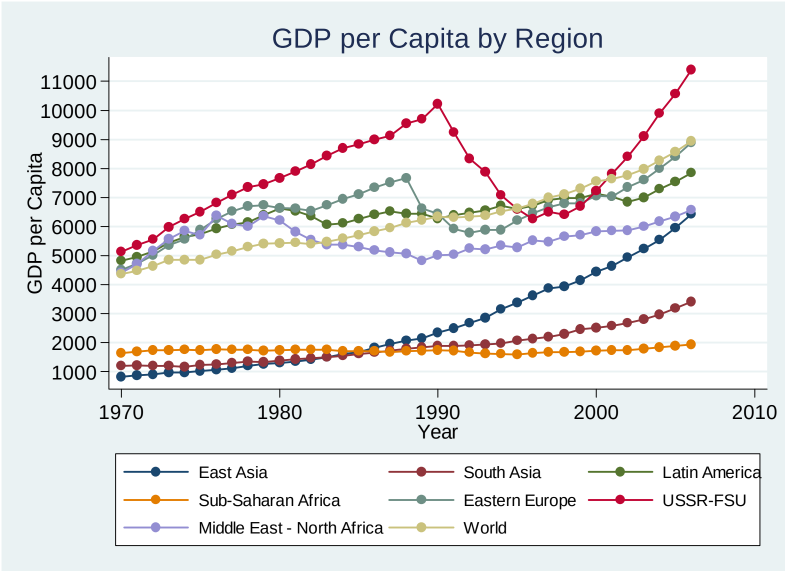


Figure 32: Poverty Rates and Counts by Region, Baseline

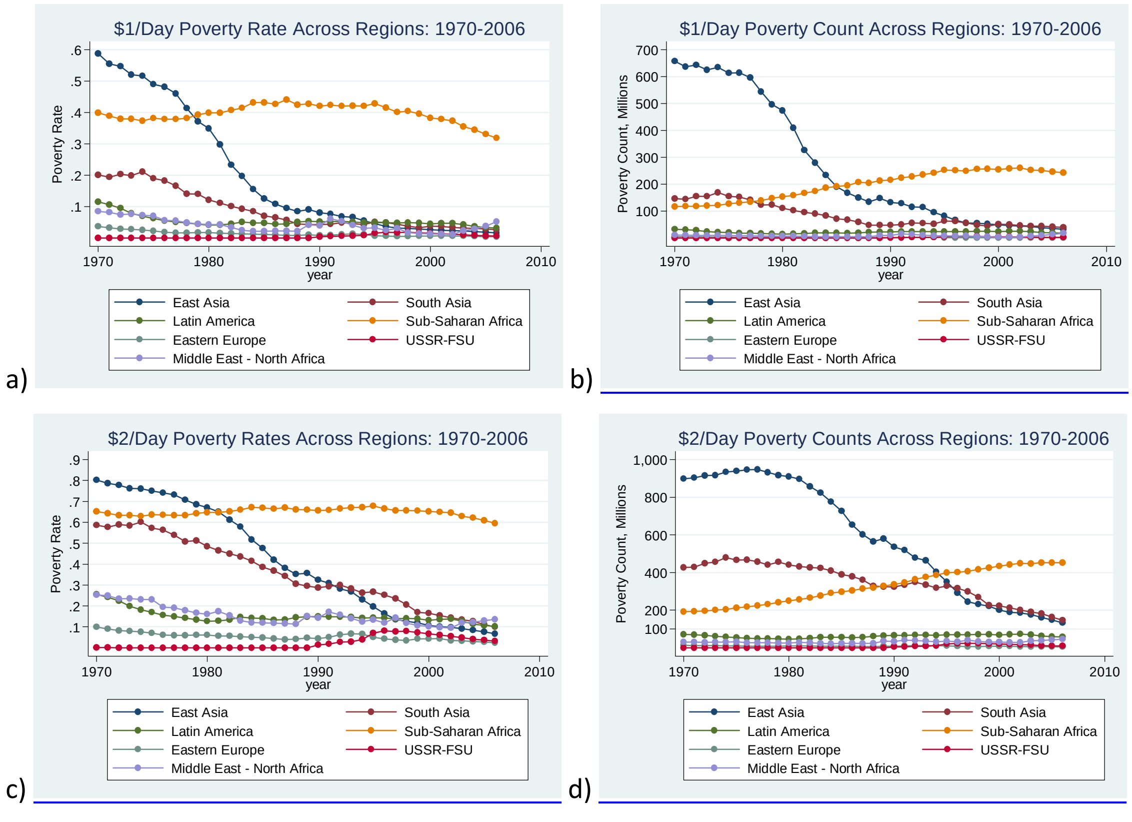
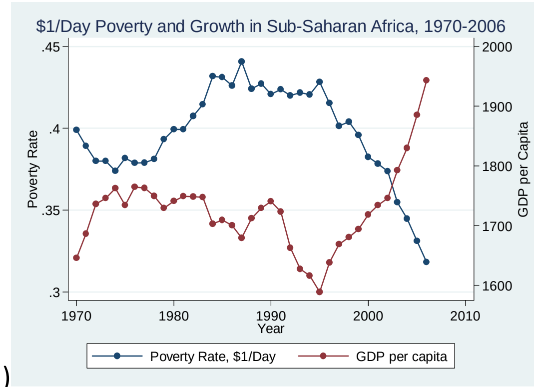
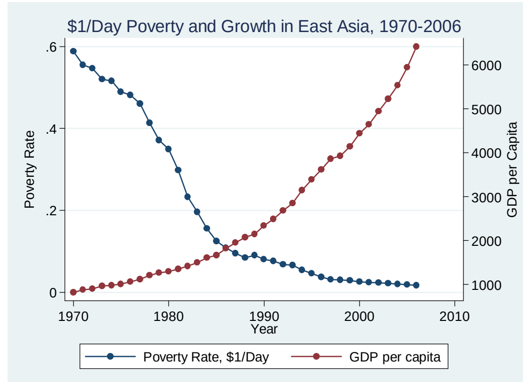


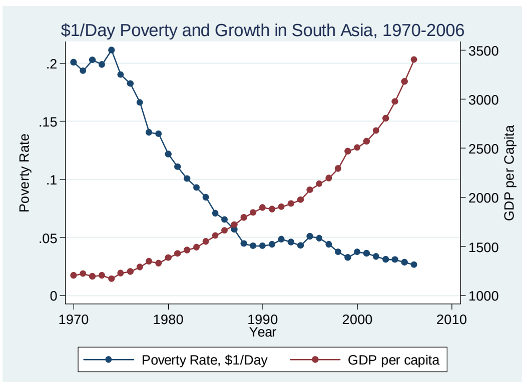
Figure 33: Mirror Graphs



a)



b)



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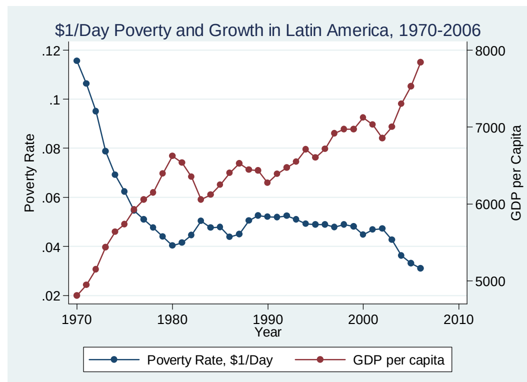

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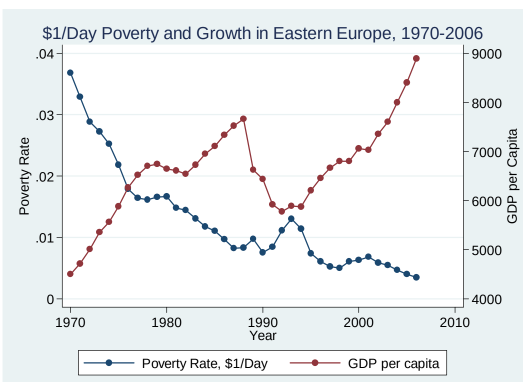
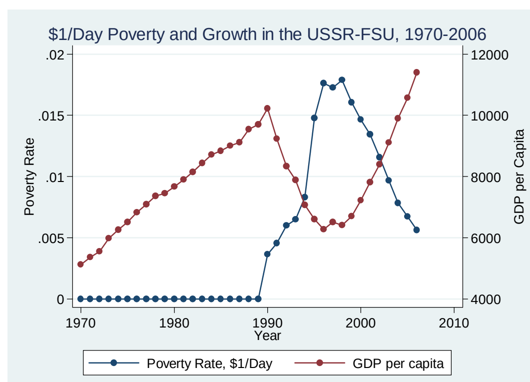


e)



f)

Figure 34: Gini Coefficient by Region, Baseline

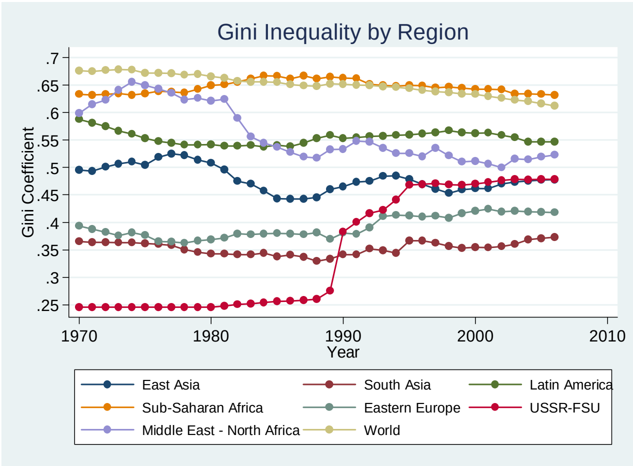
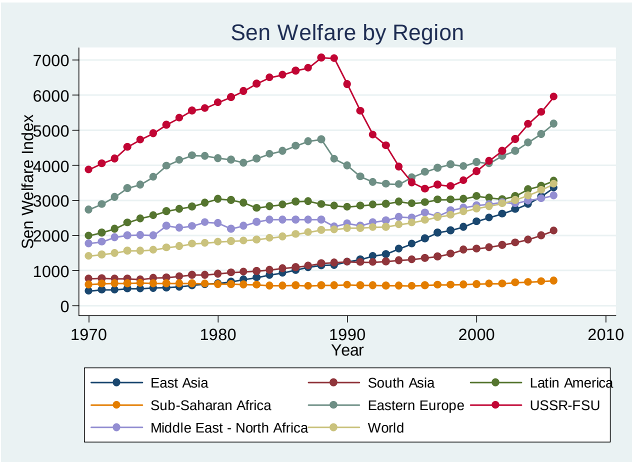
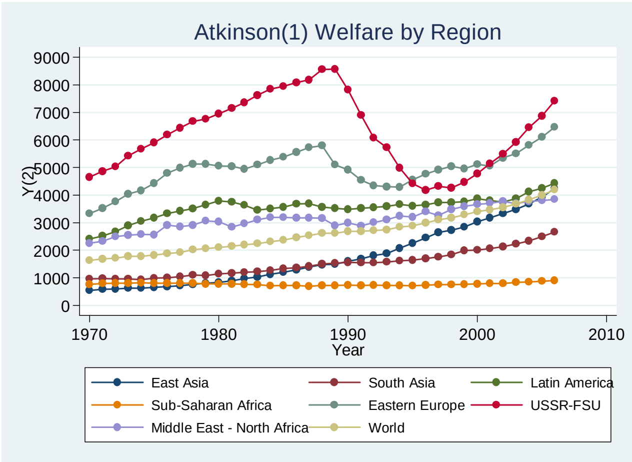


Figure 35: Welfare by Region, Baseline



a)



b)

Sensitivity Analysis:

Figure 36: $1/Day Poverty Rate

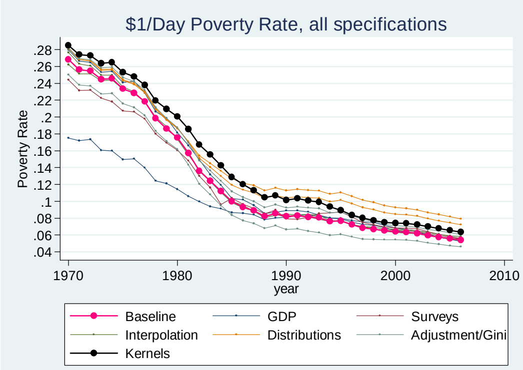


Figure 37: Gini Inequality

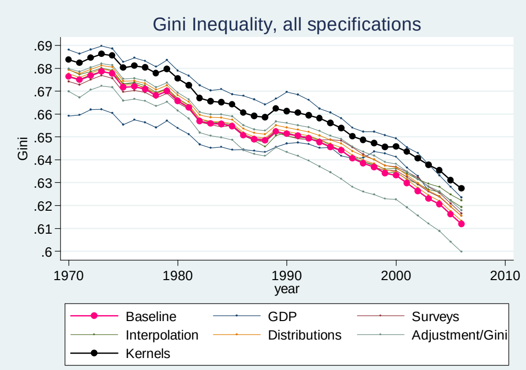


Figure 38: World Poverty Profile

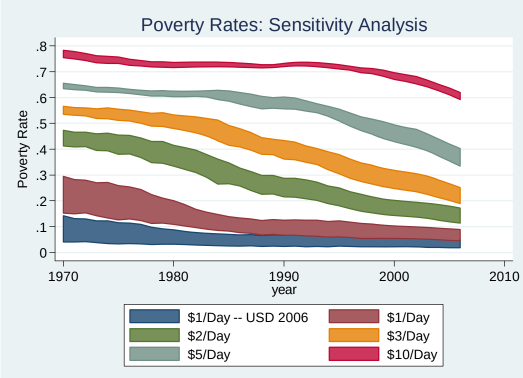


Figure 39: Regional $1/Day Poverty

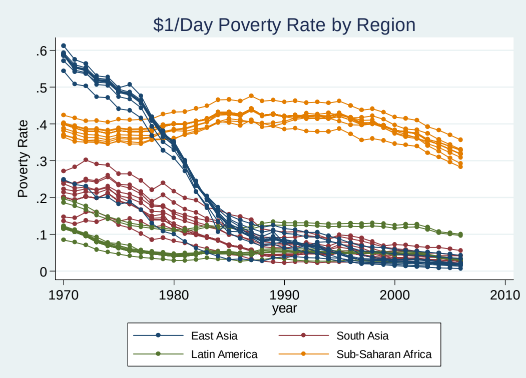


Figure 40: World Inequality Between and Within Countries, all specifications

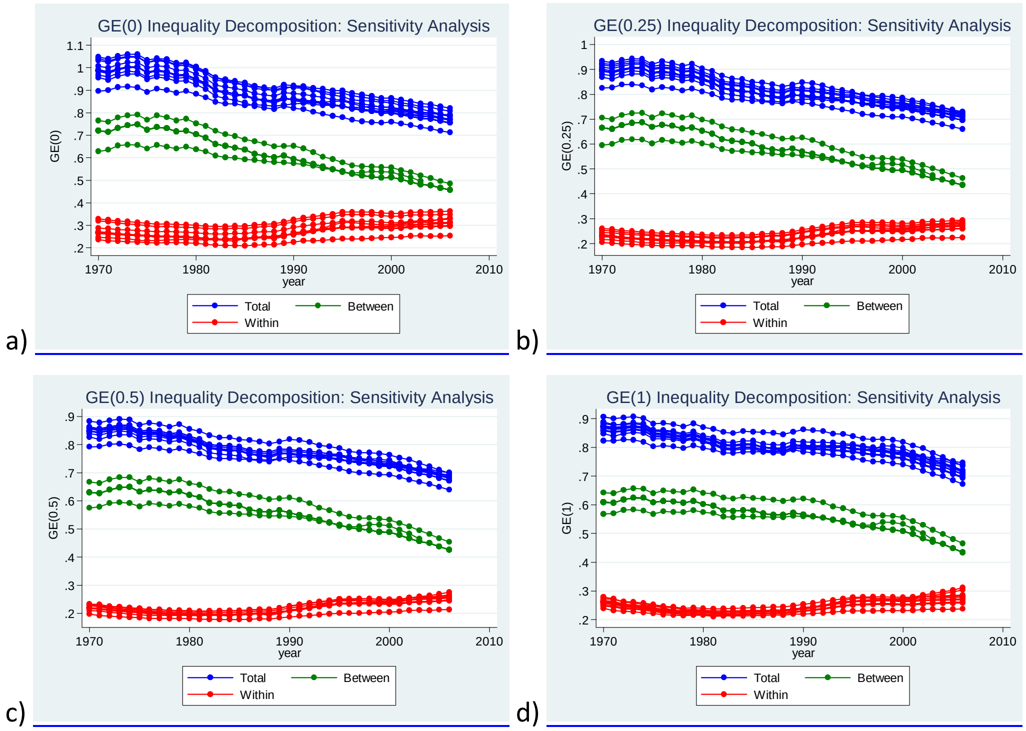


Figure 41: Survey Adjustment for Misreporting – Sensitivity Analysis

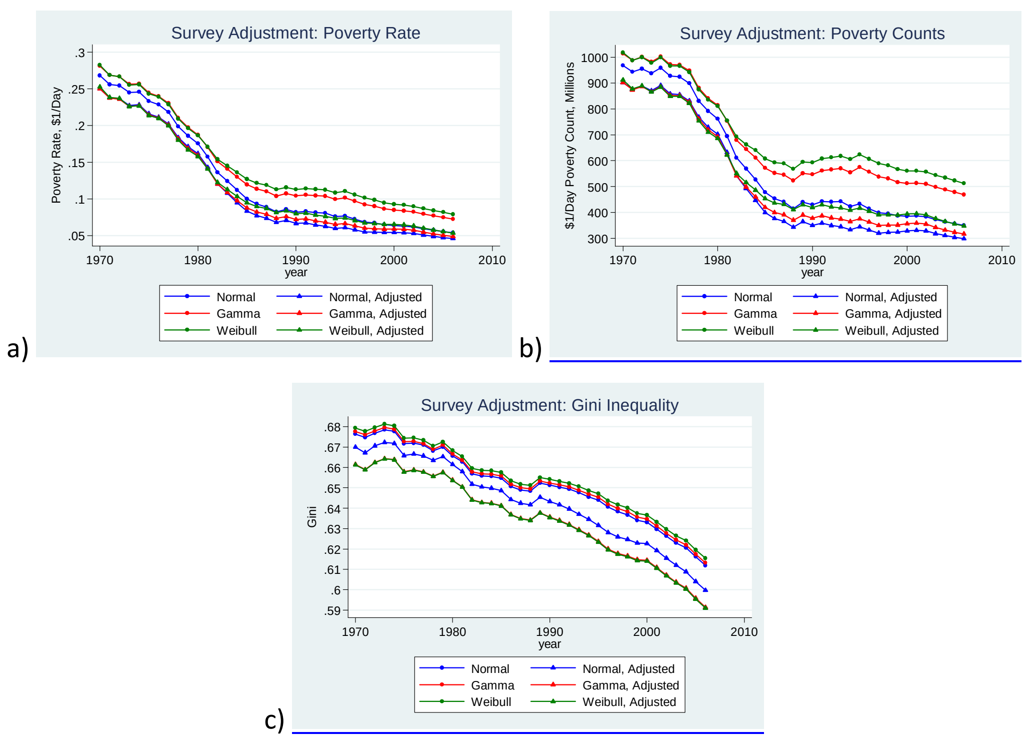


Figure 42: PPP Revision

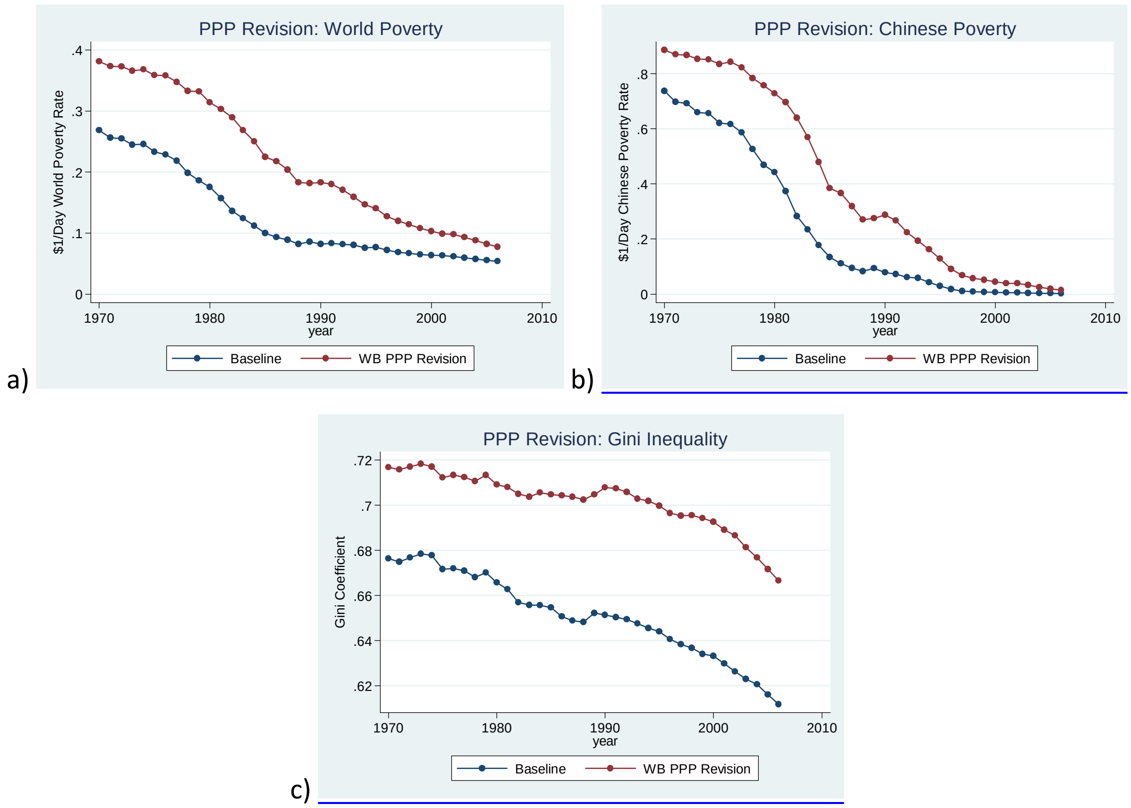


Figure 43: PPP Revision: Welfare

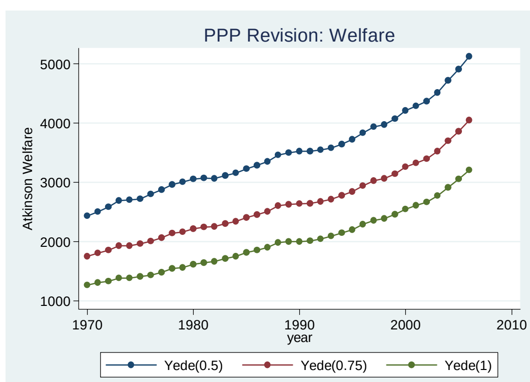


Figure 44: Growth of World Welfare Indices

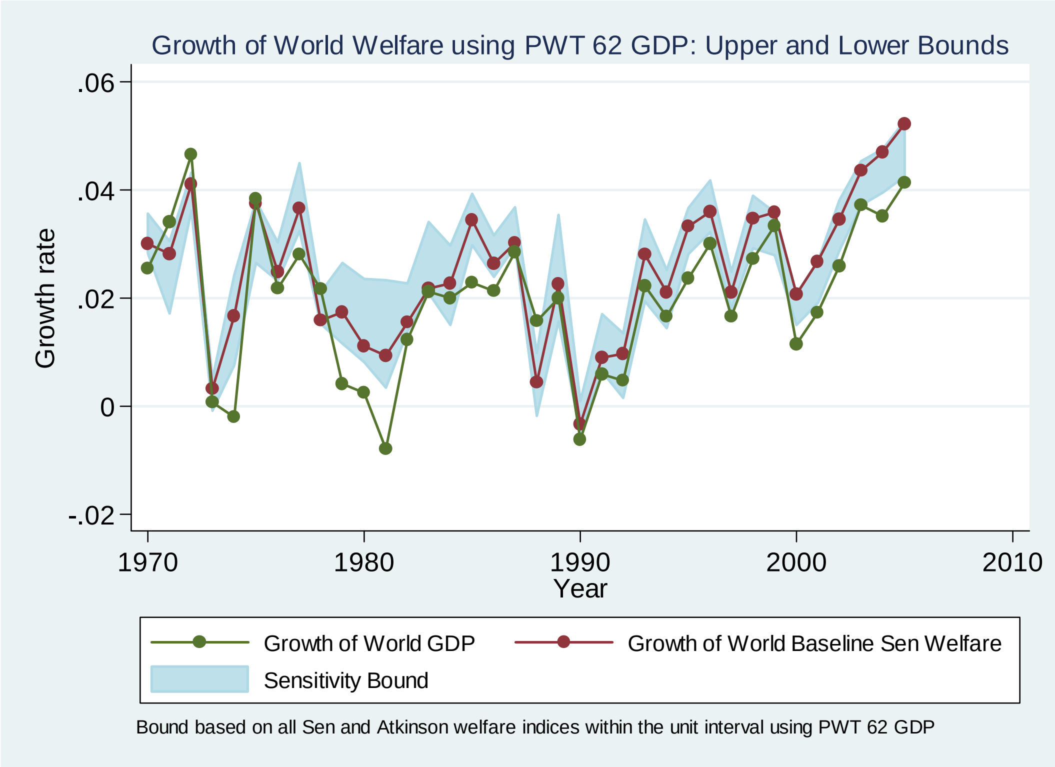


Figure 45: Pathologies Outside the Unit Interval

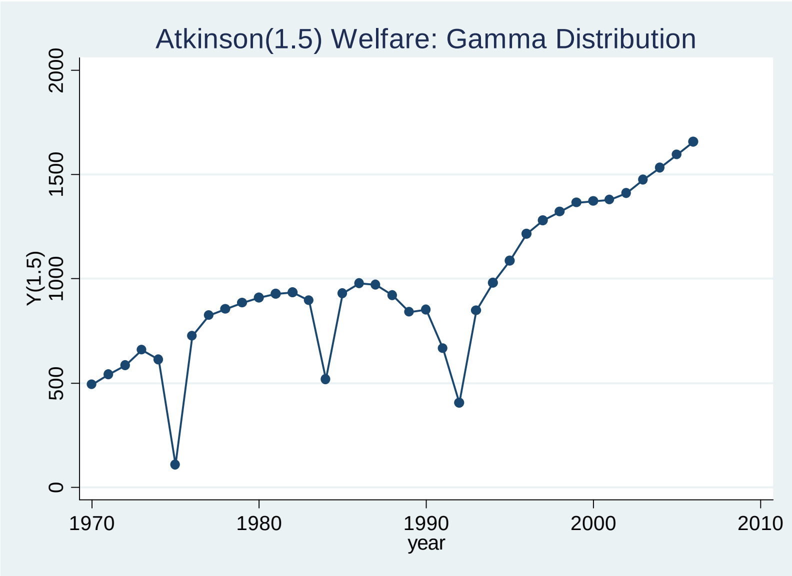


Table 1: World Poverty Rates

year	One 2006 Dollar	$1/day	$2/day	$3/day	$5/day	$10/day
1970	0.112	0.268	0.452	0.551	0.647	0.772
1971	0.099	0.256	0.445	0.546	0.643	0.767
1972	0.098	0.255	0.444	0.544	0.638	0.758
1973	0.090	0.245	0.437	0.538	0.632	0.748
1974	0.090	0.246	0.440	0.540	0.632	0.745
1975	0.081	0.233	0.431	0.535	0.629	0.742
1976	0.079	0.228	0.425	0.529	0.622	0.733
1977	0.073	0.218	0.417	0.523	0.619	0.729
1978	0.061	0.198	0.403	0.515	0.615	0.724
1979	0.054	0.186	0.398	0.513	0.616	0.723
1980	0.051	0.175	0.387	0.506	0.613	0.721
1981	0.044	0.157	0.378	0.503	0.613	0.722
1982	0.038	0.136	0.364	0.500	0.615	0.723
1983	0.036	0.124	0.352	0.494	0.614	0.723
1984	0.034	0.112	0.332	0.481	0.613	0.724
1985	0.032	0.100	0.313	0.471	0.612	0.723
1986	0.032	0.093	0.292	0.446	0.602	0.721
1987	0.033	0.089	0.275	0.429	0.593	0.720
1988	0.031	0.082	0.258	0.413	0.586	0.719
1989	0.032	0.086	0.260	0.411	0.583	0.720
1990	0.031	0.082	0.249	0.395	0.572	0.724
1991	0.032	0.083	0.248	0.392	0.568	0.727
1992	0.031	0.081	0.243	0.385	0.560	0.727
1993	0.032	0.080	0.236	0.378	0.555	0.726
1994	0.031	0.076	0.220	0.361	0.544	0.723
1995	0.032	0.077	0.214	0.349	0.531	0.719
1996	0.032	0.072	0.199	0.330	0.516	0.714
1997	0.030	0.069	0.187	0.314	0.501	0.706
1998	0.030	0.067	0.178	0.301	0.491	0.702
1999	0.029	0.065	0.168	0.286	0.476	0.693
2000	0.029	0.064	0.162	0.276	0.463	0.682
2001	0.029	0.063	0.158	0.268	0.453	0.675
2002	0.028	0.062	0.155	0.262	0.443	0.664
2003	0.026	0.059	0.150	0.253	0.430	0.652
2004	0.025	0.058	0.144	0.241	0.412	0.637
2005	0.024	0.056	0.137	0.228	0.394	0.621
2006	0.023	0.054	0.130	0.215	0.373	0.603
Change 1970-2006	-0.088	-0.214	-0.321	-0.336	-0.274	-0.169
Change 1990-2006	-0.008	-0.028	-0.118	-0.180	-0.198	-0.120
% Change 1970-2006	-79.00%	-79.88%	-71.13%	-61.05%	-42.32%	-21.90%
% Change 1990-2006	-25.46%	-34.12%	-47.53%	-45.68%	-34.70%	-16.65%

Table 2: World Poverty Counts

Year	World Population	One 2006 Dollar	$1/day	$2/day	$3/day	$5/day	$10/day
1970	3,606,646	402,693	967,574	1,629,962	1,987,121	2,334,589	2,785,442
1971	3,681,281	365,213	942,950	1,637,586	2,009,164	2,366,752	2,822,146
1972	3,755,533	368,664	955,920	1,666,018	2,042,245	2,396,004	2,845,857
1973	3,829,299	343,448	937,711	1,673,445	2,061,126	2,419,790	2,865,427
1974	3,902,750	350,454	958,633	1,715,618	2,108,719	2,465,666	2,907,470
1975	3,974,246	322,286	927,484	1,713,541	2,127,272	2,500,900	2,949,732
1976	4,044,943	321,393	924,181	1,717,843	2,139,647	2,517,629	2,964,312
1977	4,115,778	300,932	898,679	1,714,840	2,153,510	2,547,620	3,000,052
1978	4,186,440	255,870	830,624	1,686,167	2,154,863	2,574,531	3,030,065
1979	4,259,927	230,737	791,847	1,694,529	2,186,056	2,622,267	3,078,965
1980	4,344,659	219,717	761,854	1,680,143	2,196,659	2,661,686	3,131,710
1981	4,417,978	193,539	695,123	1,668,305	2,222,661	2,709,756	3,188,351
1982	4,495,734	169,397	612,067	1,635,304	2,245,641	2,764,251	3,252,617
1983	4,573,769	162,678	568,772	1,609,114	2,260,860	2,808,661	3,307,152
1984	4,709,259	161,335	527,291	1,561,759	2,265,761	2,889,123	3,409,209
1985	4,789,305	155,281	478,171	1,498,862	2,256,271	2,929,277	3,464,900
1986	4,870,966	154,605	453,356	1,420,336	2,171,876	2,932,972	3,513,686
1987	4,955,597	163,928	441,196	1,362,435	2,123,607	2,940,592	3,569,086
1988	5,043,809	154,863	414,867	1,303,719	2,084,660	2,957,778	3,624,562
1989	5,140,046	165,933	440,409	1,337,753	2,111,490	2,996,407	3,700,884
1990	5,248,768	165,105	430,138	1,305,303	2,073,429	3,000,947	3,798,261
1991	5,330,760	172,789	442,109	1,321,247	2,089,955	3,025,419	3,874,396
1992	5,416,449	168,549	440,704	1,314,692	2,084,914	3,032,235	3,939,523
1993	5,496,619	174,025	442,470	1,298,435	2,078,789	3,048,849	3,990,776
1994	5,575,946	173,362	423,733	1,228,918	2,015,035	3,032,040	4,030,692
1995	5,655,997	183,262	433,949	1,211,278	1,973,342	3,003,026	4,067,353
1996	5,734,735	180,704	414,887	1,142,259	1,893,051	2,960,022	4,093,165
1997	5,813,939	175,102	398,854	1,089,837	1,825,811	2,914,365	4,103,272
1998	5,892,413	178,231	395,419	1,049,494	1,775,601	2,892,861	4,136,967
1999	5,970,596	174,775	387,774	1,002,608	1,707,558	2,842,118	4,139,525
2000	6,047,573	172,985	385,533	982,557	1,668,508	2,797,302	4,124,598
2001	6,123,042	175,004	386,309	969,477	1,643,968	2,775,087	4,130,862
2002	6,195,290	172,520	383,528	959,422	1,621,210	2,743,872	4,112,061
2003	6,269,549	160,321	372,237	940,728	1,584,984	2,694,438	4,085,329
2004	6,343,709	158,118	364,958	913,991	1,530,142	2,616,328	4,041,035
2005	6,419,510	154,110	356,884	881,369	1,464,138	2,526,230	3,986,142
2006	6,491,236	152,203	350,436	847,011	1,392,962	2,423,597	3,915,190
Change 1970-2006	2,884,590	-250,490	-617,138	-782,951	-594,159	89,008	1,129,748
Change 1990-2006	1,242,468	-12,903	-79,702	-458,292	-680,467	-577,350	116,929
% Change 1970-2006	79.98%	-62.20%	-63.78%	-48.03%	-29.90%	3.81%	40.56%
% Change 1990-2006	23.67%	-7.81%	-18.53%	-35.11%	-32.82%	-19.24%	3.08%

Table 3: World Inequality Measures

year	Gini	(MLD) GE(0)	GE(0.25)	GE(0.5)	GE(0.75)	(Theil) GE(1)	A(0.5)	A(0.75)	A(1)
1970	0.676	0.987	0.894	0.848	0.841	0.871	0.379	0.520	0.627
1971	0.675	0.978	0.888	0.843	0.836	0.866	0.377	0.517	0.624
1972	0.677	0.992	0.898	0.850	0.841	0.869	0.380	0.522	0.629
1973	0.679	1.001	0.905	0.856	0.846	0.874	0.382	0.525	0.633
1974	0.678	1.002	0.905	0.855	0.844	0.870	0.382	0.525	0.633
1975	0.672	0.977	0.884	0.836	0.825	0.849	0.374	0.516	0.623
1976	0.672	0.985	0.889	0.839	0.826	0.848	0.375	0.518	0.627
1977	0.671	0.980	0.885	0.835	0.822	0.844	0.374	0.516	0.625
1978	0.668	0.965	0.873	0.825	0.814	0.835	0.370	0.511	0.619
1979	0.670	0.966	0.876	0.830	0.820	0.843	0.372	0.512	0.619
1980	0.666	0.949	0.861	0.817	0.807	0.830	0.367	0.506	0.613
1981	0.663	0.930	0.848	0.806	0.799	0.823	0.363	0.500	0.605
1982	0.657	0.900	0.825	0.787	0.782	0.807	0.355	0.489	0.593
1983	0.656	0.891	0.819	0.783	0.779	0.805	0.353	0.487	0.590
1984	0.656	0.884	0.814	0.782	0.780	0.809	0.353	0.485	0.587
1985	0.655	0.875	0.808	0.778	0.779	0.810	0.351	0.482	0.583
1986	0.651	0.860	0.795	0.767	0.768	0.800	0.347	0.476	0.577
1987	0.649	0.854	0.790	0.762	0.764	0.796	0.345	0.473	0.574
1988	0.648	0.849	0.786	0.760	0.763	0.797	0.344	0.472	0.572
1989	0.652	0.863	0.799	0.771	0.774	0.809	0.348	0.477	0.578
1990	0.651	0.858	0.795	0.768	0.772	0.806	0.347	0.476	0.576
1991	0.650	0.854	0.791	0.765	0.770	0.805	0.346	0.474	0.574
1992	0.649	0.847	0.786	0.762	0.768	0.805	0.345	0.472	0.571
1993	0.648	0.841	0.781	0.757	0.764	0.802	0.343	0.469	0.569
1994	0.646	0.832	0.774	0.752	0.761	0.800	0.341	0.466	0.565
1995	0.644	0.830	0.771	0.749	0.758	0.798	0.339	0.465	0.564
1996	0.641	0.818	0.761	0.740	0.750	0.791	0.336	0.460	0.559
1997	0.638	0.811	0.755	0.735	0.746	0.787	0.334	0.457	0.556
1998	0.637	0.806	0.751	0.731	0.743	0.785	0.332	0.455	0.553
1999	0.634	0.798	0.744	0.725	0.736	0.779	0.330	0.452	0.550
2000	0.633	0.799	0.743	0.723	0.733	0.774	0.329	0.451	0.550
2001	0.630	0.791	0.735	0.714	0.723	0.763	0.325	0.447	0.547
2002	0.626	0.784	0.727	0.705	0.713	0.751	0.322	0.444	0.543
2003	0.623	0.775	0.719	0.697	0.704	0.740	0.318	0.440	0.539
2004	0.621	0.772	0.714	0.692	0.698	0.732	0.316	0.437	0.538
2005	0.616	0.763	0.705	0.681	0.686	0.719	0.312	0.433	0.534
2006	0.612	0.755	0.696	0.672	0.675	0.706	0.308	0.429	0.530
Change 1970-2006	-0.064	-0.231	-0.198	-0.177	-0.166	-0.164	-0.071	-0.091	-0.097
Change 1990-2006	-0.039	-0.103	-0.098	-0.096	-0.097	-0.100	-0.039	-0.047	-0.046
% Change 1970-2006	-9.5%	-23.5%	-22.1%	-20.8%	-19.7%	-18.9%	-18.9%	-17.6%	-15.5%
% Change 1990-2006	-6.1%	-12.0%	-12.4%	-12.5%	-12.5%	-12.4%	-11.4%	-9.9%	-8.0%

Table 4: World Welfare Indices

year	Y(0.5)	Y(0.75)	Y(1)	Sen
1970	$2,708.74	$2,094.24	$1,626.35	$1,411.85
1971	$2,787.43	$2,160.28	$1,682.41	$1,454.95
1972	$2,870.59	$2,214.72	$1,716.14	$1,496.46
1973	$2,995.88	$2,305.36	$1,781.93	$1,559.17
1974	$3,000.57	$2,307.76	$1,782.24	$1,564.10
1975	$3,030.66	$2,346.65	$1,823.71	$1,590.41
1976	$3,143.69	$2,426.97	$1,878.56	$1,651.12
1977	$3,219.80	$2,489.21	$1,929.45	$1,692.62
1978	$3,331.60	$2,587.32	$2,015.57	$1,755.64
1979	$3,395.00	$2,637.09	$2,057.31	$1,783.59
1980	$3,437.84	$2,683.25	$2,102.28	$1,814.77
1981	$3,468.89	$2,722.95	$2,147.76	$1,835.11
1982	$3,482.34	$2,757.55	$2,195.77	$1,852.23
1983	$3,534.17	$2,806.11	$2,241.32	$1,881.11
1984	$3,613.59	$2,877.31	$2,306.16	$1,922.44
1985	$3,694.54	$2,950.75	$2,373.75	$1,966.64
1986	$3,807.26	$3,053.77	$2,465.06	$2,035.50
1987	$3,900.93	$3,134.77	$2,533.33	$2,089.93
1988	$4,018.84	$3,235.17	$2,620.48	$2,153.85
1989	$4,054.31	$3,251.45	$2,623.84	$2,163.30
1990	$4,144.12	$3,328.67	$2,690.51	$2,212.73
1991	$4,125.91	$3,318.51	$2,685.43	$2,205.27
1992	$4,158.68	$3,352.68	$2,721.14	$2,225.11
1993	$4,189.43	$3,383.25	$2,749.60	$2,246.64
1994	$4,297.07	$3,479.99	$2,836.07	$2,310.36
1995	$4,377.73	$3,547.79	$2,889.97	$2,359.53
1996	$4,505.96	$3,664.53	$2,994.32	$2,439.12
1997	$4,658.45	$3,795.89	$3,106.55	$2,528.54
1998	$4,747.15	$3,875.13	$3,176.38	$2,582.46
1999	$4,898.14	$4,006.41	$3,288.79	$2,673.38
2000	$5,070.86	$4,145.70	$3,398.47	$2,770.77
2001	$5,156.19	$4,222.84	$3,464.23	$2,828.70
2002	$5,273.84	$4,325.76	$3,550.08	$2,905.27
2003	$5,439.41	$4,470.14	$3,674.24	$3,007.48
2004	$5,663.75	$4,657.42	$3,826.24	$3,141.34
2005	$5,903.66	$4,864.77	$3,999.68	$3,292.25
2006	$6,187.94	$5,106.91	$4,199.08	$3,468.67
Change 1970-2006	$3,479.20	$3,012.67	$2,572.73	$2,056.82
Change 1990-2006	$2,043.82	$1,778.25	$1,508.57	$1,255.94
% Change 1970-2006	128.4%	143.9%	158.2%	145.7%
% Change 1990-2006	49.3%	53.4%	56.1%	56.8%

Table 5: Regional Poverty Rates, $1/day

year	East Asia	South Asia	Africa (SSA)	Latin America	MENA
1970	0.588	0.201	0.399	0.116	0.084
1971	0.555	0.193	0.389	0.106	0.082
1972	0.547	0.203	0.380	0.095	0.075
1973	0.520	0.199	0.380	0.079	0.076
1974	0.516	0.211	0.374	0.069	0.072
1975	0.489	0.190	0.382	0.062	0.070
1976	0.482	0.182	0.379	0.055	0.055
1977	0.460	0.166	0.379	0.051	0.055
1978	0.413	0.140	0.381	0.048	0.049
1979	0.371	0.139	0.393	0.044	0.044
1980	0.349	0.122	0.399	0.040	0.042
1981	0.297	0.111	0.399	0.042	0.043
1982	0.233	0.100	0.408	0.045	0.033
1983	0.196	0.093	0.414	0.050	0.024
1984	0.155	0.085	0.432	0.048	0.022
1985	0.125	0.071	0.431	0.048	0.021
1986	0.108	0.065	0.426	0.044	0.022
1987	0.095	0.057	0.441	0.045	0.023
1988	0.084	0.045	0.424	0.050	0.022
1989	0.090	0.043	0.427	0.053	0.042
1990	0.080	0.043	0.421	0.052	0.040
1991	0.076	0.044	0.424	0.052	0.061
1992	0.068	0.048	0.420	0.052	0.053
1993	0.066	0.046	0.422	0.051	0.041
1994	0.054	0.043	0.421	0.049	0.030
1995	0.046	0.051	0.428	0.049	0.033
1996	0.037	0.049	0.415	0.049	0.024
1997	0.031	0.044	0.401	0.048	0.031
1998	0.030	0.037	0.404	0.049	0.018
1999	0.029	0.033	0.396	0.048	0.014
2000	0.026	0.037	0.383	0.045	0.013
2001	0.024	0.036	0.378	0.047	0.011
2002	0.023	0.033	0.374	0.047	0.011
2003	0.022	0.031	0.355	0.043	0.023
2004	0.020	0.031	0.345	0.036	0.028
2005	0.018	0.029	0.331	0.033	0.038
2006	0.017	0.026	0.318	0.031	0.052
Change 1970-2006	-0.571	-0.175	-0.081	-0.085	-0.033
Change 1990-2006	-0.064	-0.016	-0.103	-0.021	0.012
% Change 1970-2006	-97.2%	-86.9%	-20.3%	-73.2%	-38.6%
% Change 1990-2006	-79.4%	-38.4%	-24.4%	-40.5%	30.3%

Table 6: Regional Poverty Rates, $2/day

year	East Asia	South Asia	Africa (SSA)	Latin America	MENA
1970	0.802	0.587	0.652	0.256	0.253
1971	0.786	0.577	0.643	0.242	0.249
1972	0.778	0.590	0.634	0.224	0.233
1973	0.762	0.584	0.634	0.199	0.236
1974	0.761	0.601	0.629	0.182	0.232
1975	0.750	0.573	0.637	0.170	0.232
1976	0.741	0.563	0.634	0.156	0.194
1977	0.731	0.539	0.634	0.149	0.190
1978	0.708	0.507	0.634	0.142	0.179
1979	0.686	0.513	0.644	0.134	0.166
1980	0.671	0.485	0.648	0.126	0.160
1981	0.650	0.466	0.647	0.128	0.174
1982	0.612	0.450	0.652	0.135	0.154
1983	0.578	0.437	0.659	0.147	0.130
1984	0.517	0.415	0.671	0.142	0.121
1985	0.476	0.386	0.669	0.141	0.119
1986	0.421	0.368	0.665	0.133	0.118
1987	0.382	0.342	0.670	0.135	0.116
1988	0.352	0.306	0.662	0.145	0.113
1989	0.356	0.296	0.660	0.149	0.152
1990	0.324	0.288	0.656	0.149	0.143
1991	0.309	0.293	0.658	0.149	0.171
1992	0.281	0.299	0.666	0.149	0.157
1993	0.270	0.283	0.671	0.146	0.141
1994	0.231	0.263	0.672	0.142	0.126
1995	0.198	0.267	0.679	0.143	0.134
1996	0.163	0.252	0.666	0.142	0.119
1997	0.135	0.235	0.657	0.139	0.144
1998	0.126	0.207	0.657	0.141	0.118
1999	0.119	0.170	0.654	0.139	0.107
2000	0.107	0.165	0.652	0.132	0.102
2001	0.100	0.154	0.649	0.136	0.097
2002	0.097	0.144	0.645	0.137	0.094
2003	0.092	0.134	0.630	0.128	0.119
2004	0.083	0.127	0.622	0.113	0.122
2005	0.076	0.112	0.609	0.107	0.129
2006	0.067	0.099	0.595	0.102	0.136
Change 1970-2006	-0.734	-0.488	-0.058	-0.155	-0.117
Change 1990-2006	-0.257	-0.189	-0.062	-0.048	-0.007
% Change 1970-2006	-91.6%	-83.2%	-8.8%	-60.3%	-46.2%
% Change 1990-2006	-79.3%	-65.7%	-9.4%	-31.9%	-5.1%

Table 7: Correlations of Major Variables to Baseline by Type of Sensitivity Analysis

	WB GDP	Maddison GDP	Single Countries	China Cons.	Nearest Neighbor	Linear	Gamma	Weibull	Optimal	Gini	Adjusted	Kernels
$1/day count, USD 2006	0.99	0.00	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98
$1/day count	0.99	0.94	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
$2/day count	0.99	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$3/day count	0.98	0.89	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.95
$5/day count	0.98	0.92	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.98	0.95
$7.5/day count	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$10/day count	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$1/day rate, USD 2006	0.99	0.93	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$1/day rate	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
$2/day rate	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$3/day rate	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$5/day rate	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$7.5/day rate	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$10/day rate	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
GE(0)	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
GE(0.25)	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
GE(0.5)	0.99	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
GE(0.75)	0.99	0.91	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99
GE(1)	0.98	0.80	0.99	0.99	0.98	0.97	0.99	0.99	0.99	0.99	0.99	0.99
Y(0.5) Welfare	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
Y(0.75) Welfare	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
Y(1) Welfare	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
A(0.5) Inequality	0.99	0.95	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
A(0.75) Inequality	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
A(1) Inequality	0.99	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Gini	0.99	0.96	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Sen	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99
P7525	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
P9010	0.99	0.95	0.98	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99

Key
>0.99
0.99>x>0.9
<0.9

Table 8: Measures of Identity of Major Variables to Baseline

	WB GDP	Maddison GDP	Single Countries	China Cons.	Nearest Neighbor	Linear	Gamma	Weibull	Optimal	Ginis	Adjusted	Kernels
$1/day count, USD 2006	0.08	1.35	0.44	0.00	0.03	0.22	0.64	0.91	0.00	0.18	0.27	0.66
$1/day count	0.06	0.89	0.28	0.02	0.03	0.04	0.34	0.50	0.00	0.10	0.15	0.21
$2/day count	0.08	0.47	0.15	0.06	0.02	0.06	0.22	0.32	0.00	0.12	0.22	0.33
$3/day count	0.13	0.63	0.15	0.09	0.03	0.08	0.14	0.21	0.00	0.15	0.28	0.48
$5/day count	0.14	0.22	0.03	0.03	0.04	0.06	0.07	0.12	0.00	0.03	0.08	0.17
$7.5/day count	0.07	0.10	0.00	0.01	0.02	0.03	0.05	0.07	0.00	0.00	0.03	0.07
$10/day count	0.03	0.08	0.00	0.00	0.02	0.03	0.02	0.02	0.00	0.00	0.01	0.06
$1/day rate, USD 2006	0.05	1.11	0.36	0.00	0.02	0.16	0.47	0.64	0.00	0.20	0.29	0.64
$1/day rate	0.10	0.75	0.23	0.01	0.02	0.04	0.21	0.32	0.00	0.12	0.16	0.22
$2/day rate	0.12	0.28	0.07	0.02	0.01	0.02	0.11	0.15	0.00	0.06	0.12	0.18
$3/day rate	0.09	0.25	0.05	0.03	0.01	0.03	0.05	0.07	0.00	0.06	0.12	0.20
$5/day rate	0.12	0.23	0.03	0.03	0.02	0.04	0.05	0.09	0.00	0.04	0.08	0.15
$7.5/day rate	0.13	0.24	0.01	0.02	0.05	0.07	0.07	0.12	0.00	0.02	0.04	0.07
$10/day rate	0.12	0.31	0.03	0.02	0.07	0.08	0.05	0.06	0.00	0.01	0.02	0.15
GE(0)	0.11	0.60	0.20	0.05	0.05	0.10	0.10	0.12	0.00	0.06	0.14	0.14
GE(0.25)	0.10	0.58	0.18	0.05	0.06	0.10	0.05	0.07	0.00	0.05	0.14	0.14
GE(0.5)	0.09	0.59	0.16	0.05	0.08	0.11	0.01	0.03	0.00	0.04	0.15	0.14
GE(0.75)	0.10	0.64	0.15	0.05	0.12	0.14	0.00	0.00	0.00	0.03	0.17	0.14
GE(1)	0.13	0.73	0.14	0.06	0.17	0.19	0.02	0.02	0.00	0.03	0.20	0.16
Y(0.5) Welfare	0.05	0.23	0.02	0.01	0.02	0.03	0.01	0.01	0.00	0.02	0.04	0.06
Y(0.75) Welfare	0.07	0.26	0.04	0.02	0.02	0.04	0.04	0.06	0.00	0.03	0.07	0.10
Y(1) Welfare	0.08	0.29	0.06	0.02	0.02	0.06	0.11	0.13	0.00	0.05	0.10	0.14
A(0.5) Inequality	0.08	0.59	0.16	0.05	0.08	0.12	0.02	0.03	0.00	0.04	0.16	0.14
A(0.75) Inequality	0.07	0.57	0.18	0.05	0.06	0.11	0.06	0.08	0.00	0.05	0.16	0.15
A(1) Inequality	0.07	0.57	0.20	0.05	0.05	0.12	0.12	0.15	0.00	0.07	0.17	0.17
Gini	0.10	0.55	0.15	0.06	0.09	0.12	0.01	0.02	0.00	0.04	0.16	0.13
Sen	0.09	0.25	0.04	0.02	0.03	0.04	0.00	0.01	0.00	0.03	0.07	0.08
P7525	0.09	0.45	0.21	0.03	0.03	0.02	0.10	0.08	0.00	0.08	0.08	0.22
P9010	0.12	0.85	0.37	0.06	0.03	0.16	0.22	0.39	0.00	0.09	0.14	0.23

Key
<0.01
0.01<x<0.1
x>0.1

Table 9: Correlation and Identity between Baseline and PPP-Revised Series

	WN Corr	WN Levels
$1/day count, USD 2006	0.9249	3.199659
$1/day count	0.9044	1.278127
$2/day count	0.7934	0.9550788
$3/day count	0.3411	1.267136
$5/day count	0.7629	0.8982319
$7.5/day count	0.9661	0.5308061
$10/day count	0.9880	0.2867584
$1/day rate, USD 2006	0.9687	3.068232
$1/day rate	0.9581	1.359933
$2/day rate	0.9633	0.6073896
$3/day rate	0.9643	0.6434812
$5/day rate	0.9313	0.7177572
$7.5/day rate	0.8368	0.7646995
$10/day rate	0.8258	0.7267156
GE(0)	0.9905	0.5678449
GE(0.25)	0.9881	0.3744607
GE(0.5)	0.9824	0.3428783
GE(0.75)	0.9662	0.4845983
GE(1)	0.9152	0.6392682
Y(0.5) Welfare	0.9995	0.401631
Y(0.75) Welfare	0.9995	0.4614342
Y(1) Welfare	0.9994	0.5083473
A(0.5) Inequality	0.9822	0.3558683
A(0.75) Inequality	0.9874	0.261631
A(1) Inequality	0.9889	0.2003507
Gini	0.9634	0.4833855
Sen	0.9984	0.5250562
P7525	0.9932	1.407715
P9010	0.9912	1.620185

Table 10.1: Correlations of Welfare Series to PWT 62 GDP

	Median	Sen	Y(0.5)	Y(0.75)	Y(1)
China and India single	0.994	0.9989	0.9996	0.999	0.9982
Linear Interpolation	0.9936	0.9993	0.9996	0.9986	0.9968
Nearest Neighbor Interpolation	0.9931	0.9992	0.9996	0.9988	0.9975
Gamma, adjusted	0.9914	0.9988	0.9995	0.9988	0.9975
Gamma, ginis	0.9925	0.9989	0.9996	0.999	0.9983
Gamma	0.9926	0.9989	0.9996	0.999	0.9982
Lognormal, adjusted	0.9927	0.9988	0.9995	0.9988	0.9975
Logormal, ginis	0.9931	0.9989	0.9996	0.999	0.9981
Baseline	0.9932	0.9989	0.9996	0.999	0.9981
Optimal, adjusted	0.9926	0.9988	0.9995	0.9988	0.9975
Optimal, ginis	0.9931	0.9989	0.9996	0.999	0.9981
Optimal	0.9932	0.9989	0.9996	0.999	0.998
Weibull, adjusted	0.9911	0.9988	0.9995	0.9988	0.9975
Weibull, ginis	0.9924	0.9989	0.9996	0.999	0.9982
Weibull	0.9925	0.9989	0.9996	0.999	0.9981
Consumption surveys for China	0.9933	0.9991	0.9996	0.9989	0.9977
Kernels	0.9932	0.999	1	0.9989	0.9976

Table 10.2: Correlations of Growth of Welfare Series to Growth of PWT 62 GDP

	Sen	Y(0.5)	Y(0.75)	Y(1)
China and India single	0.881023	0.950633	0.861218	0.72131
Linear Interpolation	0.898433	0.95923	0.875758	0.725861
Nearest Neighbor Interpolation	0.880259	0.952982	0.864105	0.714578
Gamma, adjusted	0.880593	0.95445	0.867393	0.7191
Gamma, ginis	0.888486	0.955055	0.873899	0.744737
Gamma	0.888716	0.955675	0.876675	0.75305
Lognormal, adjusted	0.878588	0.953278	0.865724	0.71813
Logormal, ginis	0.888734	0.95548	0.874766	0.74148
Baseline	0.888645	0.955983	0.876678	0.745329
Optimal, adjusted	0.878813	0.953311	0.865766	0.718158
Optimal, ginis	0.888768	0.955478	0.874715	0.741345
Optimal	0.888666	0.955978	0.876608	0.745158
Weibull, adjusted	0.87995	0.954341	0.867169	0.719364
Weibull, ginis	0.888544	0.955107	0.873555	0.742533
Weibull	0.888776	0.955647	0.876068	0.749189
Consumption surveys for China	0.889279	0.956359	0.875424	0.739567
Kernels	0.892259	0.954296	0.869731	0.72906

Table 11: Welfare Growth

11.1: World	Y(0.5)	Y(0.75)	Y(1)	Sen
Baseline	128.40%	143.90%	158.20%	145.70%
China and India single	125.60%	138.40%	149.40%	141.20%
Nearest Neighbor Interpolation	125.80%	139.80%	153.00%	141.20%
Linear Interpolation	125.70%	139.00%	150.40%	141.40%
Lognormal, Ginis	127.90%	142.70%	156.00%	144.50%
Lognormal, Adjusted	129.70%	146.00%	161.30%	148.40%
Gamma, Ginis	128.00%	142.90%	155.00%	144.70%
Gamma	128.60%	144.20%	158.50%	145.80%
Gamma, Adjusted	129.10%	145.40%	161.10%	147.20%
Weibull, Ginis	127.90%	142.40%	154.30%	144.70%
Weibull	128.40%	143.70%	157.00%	145.70%
Weibull, Adjusted	129.20%	145.40%	161.00%	147.40%
Consumption surveys for China	127.30%	141.80%	155.30%	143.50%
World Bank, China and India Single	120.30%	134.00%	146.20%	135.40%
World Bank	124.00%	140.40%	156.00%	140.90%
World Bank, China with Consumption	122.90%	138.40%	153.00%	138.70%
Maddison, China and India Single	77.30%	80.60%	82.00%	82.80%
Maddison	80.00%	85.60%	89.60%	87.20%
Maddison, China with Consumption	79.10%	84.10%	87.50%	85.50%
Kernels	126.40%	140.40%	152.60%	141.30%
PPP Revision, nearest-neighbor interpolation	108.10%	127.10%	148.50%	116.80%
PPP Revision, linear interpolation	108.30%	126.60%	146.20%	117.40%
PPP Revision	110.60%	131.00%	153.70%	120.60%
11.2: Average over Countries				
Baseline	111.30%	111.80%	112.40%	111.80%
China and India single	110.80%	111.00%	111.50%	110.70%
Nearest Neighbor Interpolation	108.70%	108.70%	109.30%	108.00%
Linear Interpolation	109.80%	112.00%	116.30%	112.90%
Lognormal, Ginis	110.10%	110.00%	110.00%	109.40%
Lognormal, Adjusted	112.90%	114.30%	116.00%	115.40%
Gamma, Ginis	110.10%	110.50%	112.90%	109.40%
Gamma	111.50%	112.80%	116.20%	111.80%
Gamma, Adjusted	112.00%	113.10%	115.10%	113.10%
Weibull, Ginis	110.10%	110.10%	111.00%	109.40%
Weibull	111.30%	112.20%	114.10%	111.70%
Weibull, Adjusted	112.10%	113.20%	115.00%	113.50%
Consumption surveys for China	111.10%	111.40%	112.00%	111.40%
World Bank, China and India Single	108.70%	109.10%	109.80%	109.00%
World Bank	109.20%	109.80%	110.70%	110.00%
World Bank, China with Consumption	109.00%	109.50%	110.20%	109.60%
Maddison, China and India Single	64.80%	65.10%	65.60%	65.20%
Maddison	65.10%	65.60%	66.20%	65.80%
Maddison, China with Consumption	65.00%	65.40%	66.00%	65.60%
Kernels	102.70%	102.20%	101.90%	101.10%
PPP Revision, nearest-neighbor interpolation	106.80%	106.70%	107.30%	106.10%
PPP Revision, linear interpolation	107.80%	109.90%	114.10%	110.90%
PPP Revision	109.70%	110.30%	111.10%	110.50%

Table 12: Poverty Reduction 1990-2006, all specifications

	East Asia	South Asia	Latin America	Africa (SSA)	MENA	World
Baseline	-79.4%	-38.4%	-40.5%	-24.4%	30.3%	-34.1%
China and India single	-72.9%	-12.9%	-40.5%	-24.4%	30.3%	-29.0%
Nearest Neighbor Interpolation	-74.5%	-44.5%	-41.4%	-26.4%	41.1%	-35.5%
Linear Interpolation	-72.7%	-9.3%	-44.9%	-30.3%	12.0%	-29.5%
Lognormal, Ginis	-77.0%	-51.7%	-39.2%	-22.3%	2.5%	-34.0%
Lognormal, Adjusted	-79.0%	-12.5%	-53.0%	-26.5%	77.2%	-31.0%
Gamma, Ginis	-62.9%	-43.2%	-22.9%	-19.9%	-23.0%	-29.0%
Gamma	-66.8%	-41.2%	-23.8%	-21.8%	-14.6%	-30.6%
Gamma, Adjusted	-73.2%	-36.7%	-36.1%	-24.1%	32.4%	-32.2%
Weibull, Ginis	-60.0%	-39.5%	-22.0%	-19.8%	-19.9%	-28.4%
Weibull	-62.8%	-39.3%	-22.5%	-21.1%	-15.6%	-30.1%
Weibull, Adjusted	-69.1%	-42.5%	-31.9%	-23.2%	17.4%	-33.0%
Optimal, Ginis	-77.0%	-51.7%	-39.2%	-22.4%	2.5%	-34.0%
Optimal	-79.4%	-38.4%	-40.4%	-24.4%	30.3%	-34.1%
Optimal, Adjusted	-79.0%	-12.5%	-52.7%	-26.6%	77.2%	-31.1%
Consumption surveys for China	-73.7%	-38.4%	-40.5%	-24.4%	30.3%	-31.8%
World Bank, China and India Single	-85.7%	-56.0%	-39.3%	-18.7%	-65.2%	-35.5%
World Bank	-91.2%	-70.3%	-39.3%	-18.7%	-65.2%	-41.0%
World Bank, China with Consumption	-86.4%	-70.3%	-39.3%	-18.7%	-65.2%	-39.0%
Maddison, China and India Single	-49.0%	-31.6%	-17.1%	-12.3%	48.4%	-13.6%
Maddison	-64.8%	-52.8%	-17.1%	-12.3%	48.4%	-22.8%
Maddison, China with Consumption	-51.7%	-52.8%	-17.1%	-12.3%	48.4%	-20.6%
Kernels	-83.4%	-60.3%	-55.1%	-15.0%	20.9%	-37.4%
PPP Revision, nearest-neighbor interpolation	-88.0%	-71.5%	-38.4%	-20.2%	-84.6%	-58.2%
PPP Revision, linear interpolation	-87.8%	-63.7%	-42.0%	-21.8%	-88.9%	-54.1%
PPP Revision	-89.8%	-71.1%	-37.6%	-18.0%	-85.9%	-57.7%