NBER WORKING PAPER SERIES

# GROWTH ELASTICITIES OF POVERTY REDUCTION

Martin Ravallion

Working Paper 30401
http://www.nber.org/papers/w30401

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2022

Helpful comments were received from Katy Bergstrom, Gaurav Datt, Ravi Kanbur, Berk Ozler, Jacques Silber, Dominique van de Walle and Bagus (Roy) Wirapati. No financial support was received for this research. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Growth Elasticities of Poverty Reduction
Martin Ravallion
NBER Working Paper No. 30401
August 2022
JEL No. I32,O15

## ABSTRACT

Thirty years ago, Nanak Kakwani provided elegant nonparametric formulae for the point elasticities of measures of poverty with respect to changes in the mean of the distribution of income, thus analytically linking the poverty measures to key macroeconomic aggregates. Numerous insights are found in Kakwani's elasticities. However, the literature on poverty and growth since then has revealed that the impacts of economic growth on poverty, as observed in practice, can be substantially lower than suggested by Kakwani's elasticities; the reasons include rising inequality, measurement errors, discrepancies between surveys and national accounts, and changing ideas about what "poverty" means in specific contexts. Nor should Kakwani's elasticities be treated as structural parameters. Rather, they can vary over time and place, and in systematic ways that merit closer attention.

Martin Ravallion
Department of Economics
Georgetown University
ICC 580
Washington, DC 20057
and NBER
mr1185@georgetown.edu

## 1. Introduction

Intuitively, one can think of any measure of poverty as being determined by both the mean of the distribution and the extent of "inequality."[2] In considering the impact of growth on such a measure of poverty, a natural and longstanding benchmark has been what can be called "distribution-neutrality," meaning that one imagines that all incomes grow at the same rate, thus keeping inequality constant.[3] For example, when Robert Lampman (the economist advising U.S. President Lyndon B. Johnson on the "War on Poverty" in the mid-1960s) projected poverty measures over time he assumed that relative distribution would remain fixed, which he thought was reasonably consistent with historical experience (Lampman 1965). This led Lampman to argue that poverty rates in the U.S. would continue to fall. Indeed, by this reckoning, poverty in America was expected to vanish by 1990. It did not.

By modern standards, Lampman's calculations seem crude. They did not draw on the analytic properties of poverty measures and nor did he have much data. Both these things had changed by 1990. In an important paper on this topic, Nanak Kakwani (1990, 1993) introduced the concept of the "growth elasticity of poverty reduction." The "Kakwani elasticity" (as it will be called here) is the proportionate change in a measure of poverty that can be expected from a given rate of growth under distribution neutrality. Kakwani provided formulae for this elasticity for various measures of poverty. He also provided formulae for the elasticity with respect to inequality. These formulae offer users an immediate, operational, answer to the question as to how much impact a given rate of growth, or change in inequality, will have on poverty.

The issue addressed by this paper is whether that answer can be trusted in practice. In a famous public debate in the history of thought on poverty, J. K. Galbraith questioned Lampman's seemingly optimistic assessment of the prospects for poverty reduction through economic growth in the U.S., arguing (essentially) that inequality would rise—that the growth process going forward would not benefit key subgroups, thus choking off the gains to poor people.[4] Looking back the last 50 years, one would have to conclude that Galbraith's pessimism

[2] Here "inequality" refers to relative inequality, as determined by the distribution of incomes normalized by the mean. While the claim is adequately intuitive, a more precise formulation will be given later.
[3] For example, Kanbur (1987) used this benchmark in measuring the "cross-over time," defined as the time it takes for the average income of the poor to rise to reach the poverty line.
[4] Here Galbraith was invoking his prior arguments in Galbraith (1958).

about the prospects for pro-poor growth in America turned out to be closer to the truth than Lampman's view. This old debate points to one obvious reason why the Kakwani growth elasticities might be overstate progress against poverty in a growing economy, namely rising inequality. As we will see, it is not the only reason.

For poor countries, the Kakwani growth elasticities for the poverty rate (the percentage of the population living below the poverty line, also called the "headcount index") are typically in the region -4 to -1, and the mean is around -2, implying that a (say) 5% rate of increase in mean income will bring about a 10% rate of decrease in the poverty rate. Some examples of my calculations of the Kakwani elasticities for the poverty rate using the most recent data available and in a neighborhood of the World Bank's $1.90 a day poverty line are Côte D'Ivoire (2015): -1.8; Ethiopia (2015): -2.2; Guatemala (2014): -2.8; India (2011/12): -3.2; Nigeria (2019): -1.6; and Zimbabwe (2019): -1.3.[5] Using instead the Watts (1968) index (which reflects distribution below the poverty line), the corresponding Kakwani elasticities are: Côte D'Ivoire: -2.1; Ethiopia: -2.6; Guatemala: -2.5; India: -4.0; Nigeria: -2.3; Zimbabwe: -2.2.

Echoing the Galbraith-Lampman debate, these elasticities appear to be quite high when one compares them to the actual, empirical, elasticities obtained by dividing the proportionate change in (say) the poverty rate by the rate of economic growth. Such empirical elasticities can be quite volatile, and so potentially deceptive, but the comparisons that have been made suggest that we do not typically, in practice, see elasticities as high as the Kakwani elasticities over reasonably long periods of time. Ram (2011) calculates an average global elasticity of poverty to growth that is less than unity—probably less than half of the global Kakwani elasticity.[6]

As examples of the discrepancies between different estimates of the growth elasticities of poverty reduction, consider the two most populous countries. My calculation above of the Kakwani elasticity for India's headcount index of -3.2 is considerably higher than found by Datt et al. (2020) using 60 years of data; indeed, the Kakwani elasticity of -3.2 for India is more than double what we have seen historically in India. Arguably, this comparison understates the difference in elasticities, given that it holds the real value of the poverty line constant. Over such

[5] These were calculated numerically by the author using the World Bank *PovcalNet* database. For the headcount index, the calculations were done in the neighborhood of the $1.90 a day poverty line, in the interval ($1.80, $2.00).
[6] Also see the estimates over time in Chakrangi and Ram (2010).

a long period it is not surprising that the national poverty lines for India have been revised upwards, further attenuating the empirical growth elasticities of poverty reduction.

The case of China illustrates this last point strikingly. Around 1985, the Kakwani elasticity for rural China using the official poverty line of that time was about -2.7. The poverty rate was about 24%.[7] Fast forward to 2011, the poverty rate judged by the official line of that year was 16%. Mean real incomes in rural China had increased by a factor of six. The empirical elasticity was about -0.1—vastly lower than the Kakwani elasticity. The main reason is that China's official poverty line had more than doubled over this period. Arguably, this upward revision made the poverty line and (hence) measures more relevant to what "poverty" means in China (Chen and Ravallion 2021). So, it can be argued that perceptions in China about how much poverty had fallen are in better accord with the -0.1 elasticity than the Kakwani elasticity of -2.7.

The present paper returns to Kakwani (1993) in the light of the many lessons learnt about poverty in the developing world since that paper was written.[8] The following section recaps the formulae for the Kakwani elasticities for growth, as well as those for inequality. Then Section 3 points to reasons why the Kakwani elasticities may deviate from what we see in practice. The growth elasticities could well be quite reliable on average for absolute poverty measures, yet also deviate substantially from reality in many specific cases, including over the longer term in a growing developing country. The discussion also points to some systematic reasons why we see the differences in growth elasticities of poverty reduction found in the literature. This includes some observations that also suggest that the Kakwani elasticities might overstate progress against poverty on average. Kakwani's elasticities of poverty to inequality may well have been reliable at the time he wrote his paper, but the rise in "high-end" inequality seen in many countries, and globally, since then casts doubt on their reliability today. Section 4 provides an alternative "Rawlsian" perspective on the extent to which the poorest benefit from economic growth. Section 5 concludes.

[7] This and other calculations in this paragraph are based on estimates found in Chen and Ravallion (2021).
[8] The working paper version came out in 1990 (Kakwani 1990).

## 2. Kakwani's elasticities

The Foster-Greer-Thorbecke (FGT) (1984) class of poverty measures opened up a class of applications in which the analytic properties of those measures could help inform development policy questions. From the mid-1980s we started to see a number of efforts to use those properties to study the impacts of economic changes and policies. An influential paper by Kanbur (1987) had derived allocation formulae for external aid across countries by exploiting the properties of the FGT measures. Besley and Kanbur (1988) had used similar methods in studying the impacts of food subsidies on FGT measures. Ravallion (1988) had used the analytic properties of the FGT measures to study the implications of income variability over time for the expected level of poverty. Various methods were developed for studying the distributional patterns of a growth process, often based on FGT measures.[9]

Another example of this line of work is the set of formulae found in Kakwani (1993) for the elasticities of poverty measures to distribution-neutral growth. The Kakwani elasticities have an undeniable analytic elegance, as they do not require much more than the actual poverty measures themselves; no parametric forms or distributional assumptions about error terms and so on are required. Kakwani derived his formulae for a general class of poverty measures. The key generic property is that the measure is homogeneous of degree zero between the mean ($\mu$) of the distribution and the poverty line ($z$), meaning that the measure can be written in the form:[10]

$$P = P(\mu/z, \boldsymbol{L}) \tag{1}$$

where $\boldsymbol{L}$ is a vector representing the Lorenz curve, capturing "inequality" by interpretation. An example of (1) is the popular headcount index of poverty (H), given by the point on the cumulative distribution function (CDF) corresponding to the poverty line. Unlike H, the many "higher-order" measures of poverty in the literature reflect distribution below the line.

Kakwani (1993) defined the growth elasticity of poverty reduction as the partial elasticity of a measure of poverty with respect to $\mu$ holding $z$ and $\boldsymbol{L}$ constant. In deriving these elasticities it is easier to work with the quantile function, denoted $y(p)$ **(**$0 \leq p \leq 1$), which is simply the

[9] See McKay (2007) for a survey of the methods developed over the 20 years following Foster et al. (1984).
[10] I follow Kakwani's (1993) notation with two differences that seem desirable, namely that (i) I denote the aggregate poverty measures as $P$ (rather than $\theta$) and the individual measure as $\pi$ (rather than $P$), and (ii) that I use $\boldsymbol{L}$ for the vector of inequality parameters rather than $m$ (as used by Kakwani), which risks confusion with the mean.

inverse of the CDF, $p = F(y)$, giving the proportion of the population with income less than $y$ (with density function $f(y)$). Then $\mathrm{H} = F(z)$. For any continuous distribution with a smooth Lorenz curve, $L(p) = \int_0^p y(x)dx\,/\mu$, it can be seen that the quantile function is related to the Lorenz curve as $y(p) = L'(p)\mu$. Thus, $z = L'(\mathrm{H})\mu$ is another way of writing equation (1), for the headcount index.

Within the generic class of measures considered by Kakwani, there is a large class of additive poverty measures (including the FGT measures), which can be written in the form:

$$P = \int_0^H \pi[y(p)/z]dp \tag{2}$$

Here $\pi(.)$ is the individual poverty measure, which is a strictly decreasing function of $y(p)/z$ with $\pi(1) = 0$ (and it can be taken that $\pi(.) = 0$ for $p > \mathrm{H}$). For the FGT class of measures ($P_\alpha$), we have $\pi(.) = (1 - y(p)/z)^\alpha$ (for $p \leq H$ and $\alpha \geq 0$). The headcount index is the FGT measure with $\alpha = 0$. While not as popular as the headcount index, two widely-used FGT measures are the poverty gap index (PG), for which $\alpha = 1$, and the squared poverty gap index (SPG; $\alpha = 2$). Another example of this class of additive measures—indeed, the oldest distribution-sensitive poverty measure—is the Watts (1968) index, for which $\pi(.) = -\,ln(y(p)/z)$.[11]

Being a partial elasticity, the Kakwani elasticity holds distribution constant, which Kakwani (1993) calls the "pure growth effect." Plainly, this requires that $\frac{\partial ln y(p)}{\partial ln\mu} = 1$, for all $p$. i.e., that the quantile function increases by the same proportion everywhere, as given by the overall growth rate. Thus, the Kakwani elasticity is:

$$\eta_P \equiv \frac{\partial P}{\partial \mu}\frac{\mu}{P} = \frac{1}{P}\int_0^H \frac{\partial \pi}{\partial (y/z)}\frac{y(p)}{z}dp < 0 \tag{3}$$

For the FGT class of poverty measures:[12]

$$\eta_\alpha = \alpha(1 - P_{\alpha-1}/P_\alpha)\ (\alpha > 0) \tag{4.1}$$

$$= -zf(z)/\mathrm{H}\ (\alpha = 0) \tag{4.2}$$

[11] Atkinson (1987) provides a more complete listing of the additive measures in the literature up to that time.
[12] The formula in (4.1) already existed in the literature, in Kanbur's (1987) derivation of the effect of multiplicative transfers on FGT poverty measures. (Kanbur did not write the formula as an elasticity, but this is a small difference.)

For the Watts index, $\frac{\partial \pi}{\partial (y/z)} \frac{y(p)}{z} = -1$, so:

$$\eta_W = -\frac{\mathrm{H}}{P^W} \tag{5}$$

Kakwani (1993) also provides the formulae for other measures including the (non-additive) Sen (1976) index. However, the above measures will suffice for the present purpose.

One immediate concern is that actual growth processes need not hold inequality constant. Of course, Kakwani understood that, and also provided elasticities w.r.t. the Gini index ($G$). There are infinitely many ways that the Lorenz curve could shift with economic growth so an elasticity w.r.t. the Gini index is not well-defined. To resolve this indeterminacy, Kakwani assumed that the Lorenz curve shifts out (or in) proportionately at all points, implying Lorenz dominance, such that the new Lorenz curve is $L(p) - \lambda[p - L(p)]$ for some $\lambda$ (positive or negative). Then we can re-write equation (1) as $P = P(\mu/z, G)$. Kakwani (1993) provides elasticities of poverty measures with respect to the Gini index when the Lorenz curve shifts in this way, $\varepsilon_P \equiv \frac{\partial lnP}{\partial lnG}$. For example, it can be shown that, for the FGT poverty measures (in obvious notation), $\varepsilon_\alpha = \eta_\alpha + \alpha(\mu/z)P_{\alpha-1}/P_\alpha$ (Kakwani 1993). Kakwani also proposes a "trade-off index" given by the ratio of the elasticity with respect to the Gini index to that w.r.t. the mean, i.e., the trade-off is $\varepsilon_P/\eta_P$. It can be readily shown that the trade-off index for the FGT measures takes the form:

$$\frac{\varepsilon_\alpha}{\eta_\alpha} = 1 - \frac{\mu}{z} \ (\alpha = 0) \tag{6.1}$$

$$= 1 - \frac{\mu}{z}\left(\frac{P_{\alpha-1}}{P_{\alpha-1} - P_\alpha}\right) \ (\alpha > 0) \tag{6.2}$$

Thus, as the mean rises (relative to the poverty line), redistribution becomes more effective (in elasticity terms) relative to growth (i.e., more negative $\varepsilon_\alpha/\eta_\alpha$). (And in very poor settings, with $\mu < z$, there is no trade-off for the headcount index.)

A convenient feature is that once one has the poverty measures, the formulae for Kakwani's elasticities are very easy to implement. A possible exception is for the most popular measure, the headcount index, which also requires the value of the probability density function at the poverty line, which is not something practitioners normally calculate. However (given the homogeneity property in (1)), the Kakwani elasticity for the headcount index is simply -1 times the elasticity of the cumulative distribution function with respect to the poverty line when evaluated at the poverty line (equation 4.2). With large sample micro data, a computationally easy way to estimate $\eta_0$ is to calculate the headcount index slightly below the line ($z - \epsilon$ for some $\epsilon > 0$) and slightly above ($z + \epsilon$), and estimate the elasticity as:

$$\hat{\eta}_0 = \frac{1-[F(z+\epsilon)/F(z-\epsilon)]}{2\epsilon/(z-\epsilon)} \tag{7}$$

(The choice of the bandwidth, $2\epsilon$, will depend on the sample size.) If instead one is using a parameterized Lorenz curve or CDF calibrated to tabulated data, then there will be a corresponding parametric form for the density function.[13]

## 3. What have we learnt about growth elasticities since Kakwani (1993)?

Other ways of estimating growth elasticities of poverty reduction have emerged, including using an econometric model for poverty measures (as in Fosu 2017, and Bergstrom 2020). As shown by Bergstrom (2020), one can derive analytic formulae for the elasticities under the assumption that income is log normally distributed (although, from the perspective of most users, these formulae are rather more complex than the Kakwani elasticities, which hold more generally). Semi-elasticities have also been used in some of the literature.[14] I will not go into these alternatives here, but focus on the Kakwani elasticities.

Table 1 provides my estimates of the Kakwani growth elasticities for two FGT poverty measures, the poverty gap and the squared poverty gap, for the regions of the developing world (using the World Bank's classification scheme) for selected years since 1990. The World Bank's international poverty line of $1.90 a day is used. Two observations are notable: First, we tend to see rising (absolute) Kakwani elasticities over time, alongside falling poverty measures. For example, for East Asia, the elasticity for $PG$ rose from (minus) 1.75 in 1990 to 4.26 in 2018. Second, for regions and years for which the poverty measures are relatively high, we tend to see a higher elasticity for SPG than PG, but the ranking reverses at low values of the poverty measures.

[13] Datt and Ravallion (1992) provide formulae for two parametric forms. Bresson (2009) provides formulae for the Kakwani elasticities for a variety of specifications and discusses estimation issues when using grouped data.
[14] See, for example, Klasen and Misselhorn (2008) and Arndt et al. (2017).

Both observations are illustrated in Figure 1, which plots the Kakwani elasticities for East Asia and the Pacific (EAP) and Sub-Saharan Africa (SSA) for all years with estimates in *PovcalNet*. We see the higher (absolute) elasticities for the squared poverty gap than the poverty gap, except when the poverty rates get very low, and we see the lower elasticities (for both measures) for years with lower poverty rates. Also notice that the elasticities are lower for SSA; the discussion will return to this point.

The rest of this section discusses the Kakwani elasticities (for growth and inequality) further, in the light of lessons from the literature and the development experiences of countries over the 30 years since Kakwani's paper was written. The discussion will refer to Table 1 and Figure 1 along the way,

***Distributional changes:*** While the Kakwani growth elasticities are insightful, their relevance in practice depends (of course) on whether growth is in fact distribution-neutral, and (if not) whether Kakwani's assumption about how the Lorenz curve shifts is realistic.

With the accumulation of survey data for developing countries, one of the stylized facts to emerge by the early 2000's is that observed growth processes tend to be distribution-neutral on average (Ravallion 2001; Dollar and Kraay 2002; Ferreira and Ravallion 2009). In other words, inequality increases about half the time in growing developing countries and decreases for the other half.[15] In a recent data set I compiled from the World Bank's *PovcalNet* site I found only a small (positive) correlation between growth rates of mean consumption or income in surveys (measures in constant prices and at purchasing power parity across countries) and changes in inequality (measured by the Gini index) between the same two surveys, namely $r = 0.18$.

The finding of distribution-neutrality on average has a striking implication for measuring the impact of growth on poverty. Consider the log differential under the Kakwani assumption about how Lorenz curves shift, $dlnP = \eta_P dln\mu + \varepsilon_P dlnG$. Then, on treating the distributional measures (poverty and inequality) as random variables, we can take expectations to obtain:

[15] Recall that "inequality" refers here to relative inequality. If instead one uses the absolute Gini index, then a strong positive correlation with the rate of growth is more-or-less inevitable; Ravallion (2021a) provides further evidence on this point.

$$E(dlnP|dln\mu) = \eta_P dln\mu + \varepsilon_P E(dlnG|dln\mu) \quad (8)$$

Given the empirical finding that changes in inequality are orthogonal to growth rates, we can set $E(dlnG|dln\mu) = 0$ in equation (8). Thus, the expected change in the poverty measure is obtained simply by multiplying the Kakwani growth elasticity by the growth rate, $\eta_P dln\mu$.

However, while this holds on average, there is a wide variance in practice, so the average may be deceptive (Ravallion 2001). Finding that growth in the mean is distribution-neutral on average is perfectly consistent with large distributional changes in both directions across countries. Thus, whether inequality is in fact rising or falling during a spell of growth matters greatly to the outcomes for poverty reduction.

There are signs in the new Millennium that the correlation between changes in inequality and rates of growth among developing economies is increasing. For example, in an earlier compilation of data across countries, Ravallion (2007) calculated that the correlation coefficient between proportionate changes in the Gini index and rates of growth in mean income is -0.13 (though not statistically significant at even the 10 per cent level). Since the samples of countries with the required data have changed, we cannot rule out sample selection bias in comparing these estimates over time. Nonetheless, it is clear that we are seeing new signs in recent times of rising inequality in growing developing economies, including a number of the most populous ones (China, India, Indonesia). This points to a clear warning in using the Kakwani elasticities.

The fairly weak overall correlation between growth rates and changes in inequality naturally implies that absolute poverty measures will tend to fall with growth. This was demonstrated in Ravallion (1995), which estimated the growth elasticity of poverty reduction allowing inequality to change consistently with the data. Regressing proportionate changes in the poverty rate on the growth rates of mean income, Ravallion (1995) estimated an average elasticity of -2.4 (with a standard error of 0.49, n=16). In a recent update using many more observations (n=118), I compared the proportionate changes in the headcount index of poverty using the World Bank's international line with growth rates in the survey mean using the longest available time periods between surveys. The overall average elasticity (based on a regression of the proportionate changes on the growth rates) is -2.2 (with a standard error of 0.27).

If inequality changes during the growth process, can we rely on Kakwani's elasticities w.r.t. the Gini index? This is testable. Ravallion et al. (1991) found that Kakwani's assumption provided a good fit to how global Lorenz curves had been evolving up to the 1980s, although specific countries could see changes in distribution that looked very different to Kakwani's assumption. However, globally, and for many countries, things look different now, with the rise in "high-end" inequality (especially so when one allows for underreporting and selective survey compliance by the rich). The global Lorenz curves for 1988 and 2008 constructed by Lakner and Milanovic (2016) indicate an intersection with an outward shift for the upper 15% or so of the global distribution, and inward shift below that (as shown in Ravallion 2018). Globally (and no doubt for many countries), Lorenz dominance has not held since Kakwani wrote his paper, so his elasticities with respect to the Gini index may not match the current reality. When feasible, practitioners should check whether the Kakwani assumption holds in specific cases.

***Changing elasticities:*** Armed with growth elasticities of poverty reduction, users have sometimes been tempted to treat them as constants—essentially, as structural parameters.[16] This was never obviously true since the elasticities are functions of all the same variables that enter equation (1), namely the mean relative to the poverty line and the parameters of the relative distribution, interpretable as "inequality." Soon after Kakwani's paper appeared it was evident empirically that the Kakwani elasticities could vary quite widely (Lipton and Ravallion 1995).

It is instructive to study why we see this variation. One way of doing so is to note that the Kakwani growth elasticity is a share-weighted average of the individual income elasticities of poverty:

$$\eta_P = \int_0^H s(p)\eta_P(p)dp \tag{9}$$

where the weights are $s(p) \equiv \pi(y(p)/z)/P$ and $\eta_P(p) \equiv \partial ln\pi/\partial ln(y/z)$ is the individual growth elasticity. Given the share-weights, the distribution of income below the poverty line will play an important role, yielding different weights and hence different Kakwani elasticities depending on the place and time. Consider again the Watts index, for which $\eta_W(p) = 1/ln(y(p)/z) < 0$ for $y(p) < z$. A distribution with most of the poor clustered a little below the

[16] For example, in their simulations of optimal aid allocation, Collier and Dollar (2002) assume a constant elasticity of -2 across all developing countries. The authors do this "for simplicity" (p.1484) although from their own tabulations it is clear that they could have relaxed this assumption easily using the results of Kakwani (1993).

poverty line will have a higher (more negative) Kakwani elasticity than one where they are concentrated at the lowest, survival, level—the floor to living standards. This is hardly surprising; growth will need to do a heavier lift when the bulk of the poor are all near destitution than when they are all close to the line. However, the observation warns us against assuming that the elasticity is constant, even for a given country. In short, the Kakwani elasticities should not be thought of as "structural parameters" for a given country or region.

The literature since Kakwani (1993) has explored the ways in which the growth elasticities of poverty reduction vary (Ravallion 1997; Bourguignon 2003; Heltberg 2004; Son and Kakwani 2004; Wieser 2011; Ram 2011). Some systematic patterns have emerged. The role of the initial level of inequality is intuitive; if growth is distribution neutral on average, then the higher the initial level of inequality, the lower the share of the gains from growth that will tend to go to poor people. In practice, the differences in the growth elasticities can be huge, between around -5 to -4 for low inequality countries to close to zero for high-inequality countries (Ravallion 1997, 2001). Systematic differences also underlie the differences in income inequality. For example, a likely explanation for the empirical fact that the growth elasticities of rural poverty reduction are so much higher in China than India is that the inequality in access to agricultural land is much lower in China (Ravallion 2011).

One can also define and estimate sectoral elasticities of poverty to growth, which can help us understand how the pattern of growth impacts on poverty.[17] The sectoral pattern—urban versus rural, and by sector of output in the national accounts—has been identified as a key factor underlying the differences in the rate of poverty reduction at a given rate of growth. In the studies that have been done of this issue, one can generally reject the null hypothesis that it is only the overall rate of growth that matters, when tested on an encompassing regression of the rate of poverty reduction on the (share-weighted) rates of growth by sector.[18]

The growth elasticities can also be expected to vary with the mean. Consider the effect of a distribution-neutral growth process on the Kakwani elasticities for the Watts and FGT indices for $\alpha > 0$. It is readily verified that the effect on the Kakwani elasticities is given by:

[17] See Kakwani (1993), Ravallion and Datt (1996), Ravallion and Chen (2007) and Berardi and Marzo (2017).
[18] See Ravallion and Chen (2007) and Montalvo and Ravallion (2010) for China and Datt et al. (2020) for India, and the cross-country study by Loayza and Raddatz (2010). Further discussion can be found in Ravallion (2011).

$$\frac{\partial \eta_\alpha}{\partial ln\mu} = (\eta_{\alpha-1} - \eta_\alpha)(\eta_\alpha - \alpha)\ (\alpha > 0) \tag{10.1}$$

$$\frac{\partial \eta_W}{\partial ln\mu} = (\eta_0 - \eta_W)\eta_W \tag{10.2}$$

As noted, when poverty measures are high we tend to find empirically that $\eta_{\alpha-1} - \eta_\alpha > 0$ (as seen, for example, in Table 1) and a similar pattern is found for the Watts index, i.e., $\eta_0 - \eta_W > 0$.[19] Thus, under such a growth process, we tend to see a rising (more negative) Kakwani elasticity, implying an acceleration out of poverty as a very poor economy grows as long as it does so without a rise in inequality. Conversely, as a poor economy contracts even further, it tends to get harder to reduce poverty through growth. Similar observations apply to countries at different levels of economic development. As we saw in Table 1 for regions of the developing world, the Kakwani elasticities tend to rise (in absolute value) as poverty rates fall.

As an example, consider, Côte D'Ivoire, which was the country that Kakwani (1993) used to illustrate his elasticities. At a similar poverty line to the $1.90 a day line, Kakwani calculated a growth elasticity for the headcount index of -2.9 for Côte D'Ivoire in 1985, while my calculation indicates an elasticity of -1.8 in 2015 (Introduction). Côte D'Ivoire is a country seeing rising poverty measures over this period. The changes in distribution have depressed the (absolute) elasticity to growth. In a cruel irony, the fact that there is more poverty now in Côte D'Ivoire is likely to make it even harder to reduce poverty through economic growth.

Côte D'Ivoire is somewhat unusual, and many other countries have (thankfully) seen a decline (often large) in absolute poverty measures since Kakwani wrote his 1993 paper. Using the World Bank's fixed international line of $1.90 a day, the poverty rate for the world excluding the high-income countries fell from 44.6% in 1990 to 10.7% in 2017—a 75% decline.[20] The proportionate rates of decline were even larger for higher-order measures; for example, the SPG fell by 79%. As noted, it is quite common for the higher-order measures to fall faster, and for Kakwani elasticities to rise as overall poverty measures fall.

[19] Notice that it is not true in general that $\eta_\alpha < \eta_{\alpha-1}$. Proposition 2 in Son and Kakwani (2004) makes this claim on theoretical grounds (for $\alpha > 0$), but there is a mistake in the proof. (This is explained in a mathematical note available from the author.) Typically, one finds that $\eta_\alpha < \eta_{\alpha-1}$, but exceptions are possible.

[20] These numbers are from the World Bank's *PovcalNet* data site, accessed in August 2021.

Consider, for example, Indonesia, which has seen its $1.90 a day poverty rate fall from 69% in 1984, to 35% in 2000, and 6% in 2015. Across these same three years, the Kakwani growth elasticity for the Watts index rose appreciably, from -1.9 in 1984 to -3.7 in 2000 and -5.5 in 2015. Thus, Indonesia had the potential for an "acceleration" out of absolute poverty, whereby the same growth rate can achieve larger proportionate declines in the poverty measure over time as long as the growth process did not come with rising inequality. This insight is missed (of course) if one assumes that the elasticity is constant. However, recall that Indonesia is also one of the cases with rising inequality since around 2000. Over the 30-year period, the Gini index for Indonesia initially fell (from 0.324 in 1984 to 0.286 in 2000) but then rose appreciably, to 0.397 in 2015. The rising inequality in the post-2000 period naturally slowed the acceleration, though a substantial reduction in absolute poverty measures was still evident.

Assessments of country and regional performance against poverty need to be aware that the Kakwani elasticities can vary systematically. For example, as already evident from Figure 1, and has been noted before, the region of Sub-Saharan Africa has had a lower longer-term rate of progress than East Asia.[21] However, the initial depth of poverty is higher in SSA than other regions, including East Asia. Following the above reasoning, this difference in initial distribution will tend to yield lower growth elasticities of poverty reduction. To put the same point another way, SSA would need an even higher growth rate than East Asia to attain the same rate of progress against poverty. This gives a new perspective of the differences in performance against poverty; a lower rate of progress against poverty in SSA could be considered equally successful to East Asia when one takes account of the difference in the initial distributions.

The combined effects of a low initial mean and high initial inequality can make it especially hard to reduce poverty through economic growth. Empirically, this combined effect can be summarized well by an interaction effect between the initial level of poverty and the growth rate (Ravallion 2012). Indeed, once one controls for the distribution-corrected growth rate—one minus the initial poverty rate times the growth rate—the ordinary growth rate has little or no extra explanatory power for rates of progress against poverty across countries.

[21] See, for example, Chen and Ravallion (2010).

The policy environment can also influence the growth elasticities of poverty reduction (via $\mu/z$ and $\boldsymbol{L}$). An example is found in Datt et al. (2020) which studies the evolution of various measures of absolute poverty over 60 years in post-independence India. This included a 20-year period of liberalizing economic reforms, starting in 1991. Datt et al. find that progress against poverty was negligible until the mid-1970s, due to both low growth and a low growth elasticity of poverty reduction. A downward trend in poverty measures emerged from the mid-1970s. A key finding is that the pace of poverty reduction accelerated in the post-reform period, even though the post-reform growth process generated higher inequality. Higher growth rates helped, but so too did the change in the growth elasticities, especially due to the stronger inter-sectoral linkages in the growth process whereby urban economic growth brought larger benefits to the rural poor, as well as the urban poor. With these changes, the sectoral pattern of growth has mattered less in India in the new Millennium than in the pre-reform period.

These observations are instances of a more general point that distribution and growth are not independent, especially when key markets (such as for credit) are imperfect, and even absent (Bourguignon 2004). The key implication for the present purpose is that the average Kakwani elasticity will almost certainly have to be scaled down, and quite a lot, in high inequality countries. Even if inequality does not change during a spell of growth, the level of that inequality matters to how much impact that growth will have on poverty.

***Measurement errors:*** Growth elasticities of poverty reduction are also affected by measurement errors in surveys. Generally, we expect that surveys underestimate both the mean income and the degree of inequality (depending on how that is measured). Both effects can arise from the tendency of the rich to understate their true incomes, or not participate in surveys (Ravallion 2021b). Also, intra-household inequality is typically ignored in estimating the distributions of income; all household members are assigned the income per capita of that household. This is obviously wrong, though we rarely know how much so; the limited evidence available suggests a sizeable error in standard measures of inequality (Haddad and Kanbur 1990; De Vreyer and Lambert 2021).

The tendency to both underestimate the mean and underestimate inequality can be expected to lead practitioners to overestimate the Kakwani elasticity (suggesting it is more negative than it is in reality).[22] Growth will seem more effective than it really is. We will rarely know how far wrong we are due to such errors. The errors contaminate both the analytic and empirical elasticities.

***Relaxing constant elasticities:*** There are options that do not assume constant elasticities, or even require any estimation of elasticities. Indeed, we don't need the Kakwani elasticities to isolate the contribution of growth to poverty reduction. A general decomposition for changes in poverty measures was proposed by Datt and Ravallion (1992). This had been devised prior to Kakwani (1990) for the World Bank's (1990) *World Development Report* on Poverty, which used the method for Indonesia (as documented in Ravallion and Huppi 1991).[23] To understand the more general decomposition, consider the case of two years. To calculate the contribution of growth in the mean to the poverty measures holding the base year Lorenz curve constant all we need to do is scale up all incomes in the base-year (as found in the survey data) by the same growth rate and re-calculate the poverty measures on this new (synthetic) distribution. That gives us the growth component. Similarly, to calculate the redistribution component, we can create another synthetic distribution, but this time it is the final year Lorenz curve but using the base-year mean.[24] Thus, comparing two dates, 1 and 2, and using the first date as the reference year for all components, the Datt-Ravallion decomposition takes the form:[25]

$$P_2 - P_1 = [P(\mu_2/z, \boldsymbol{L_1}) - P_1] + [P(\mu_1/z, \boldsymbol{L_2}) - P_1] + \text{interaction effect} \qquad (11)$$

The first term in square brackets is the growth component and the second term is the redistribution component. Note that there is an interaction effect, which stems from the fact that the growth effect depends on the Lorenz curve, and similarly the redistribution effect depends on the mean.[26] (In other words, the poverty measure is not additively separable between its two components.) It can be seen that none of this requires explicit elasticities (constant or otherwise),

[22] This argument relies on the prior empirical generalizations, for which exceptions are possible.
[23] Kakwani (1993) references Ravallion and Huppi (1991), but claims that the latter used a regression method to derive their decompositions and argues that his method is preferable. However, no such regression-based decomposition was used in Ravallion and Huppi. Rather, they used the Datt-Ravallion method.
[24] In other words, one multiplies all incomes in the final year by the ratio of the base-year mean to the final year mean.
[25] For examples of this decomposition see Ravallion and Huppi (1991), Kraay (2006), Ravallion and Chen (2007), and Datt et al. (2021).
[26] Further discussion of this interaction effect can be found in Ravallion (2016a, Box 5.14). Note that the decomposition depends on the choice of reference, as discussed in Datt and Ravallion (1992).

though average elasticities (proportionate changes in poverty measures divided by proportionate changes in the mean) can always be calculated *ex-post* if desired.

The same idea can be applied to the task of forecasting poverty measures under distribution-neutrality. Again, no assumption of constant point elasticities is required; one simply scales up (or down) each level of income in the base data by the same growth factor, and then one recalculates the poverty measure.[27]

***Changing poverty lines:*** I don't think many people around 1990, including Kakwani, anticipated the huge reduction in extreme absolute poverty we have seen in the developing world, which came with substantial growth in mean incomes, especially since 2000. That growth brings into question another assumption in the Kakwani elasticities, namely that the poverty line is fixed in real terms, giving what are often called "absolute poverty measures."

Alongside this overall growth, we have tended to see rising national poverty lines. Using panel data of implicit national poverty lines, Ravallion (2020) regressed the log poverty line on the log mean including country fixed effects (so the elasticity is only identified from the time series variation).[28] The average elasticity of the national poverty lines to the mean is 0.52 (with a robust s.e.=0.04; n=598). This is both significantly less than unity—as for the "strongly relative" measures favored by some, in which the poverty line is set at a constant proportion of the mean or median—and significantly different from zero, as in the absolute measures. Thus, national poverty measures tend to be what Ravallion and Chen (2011) dub "weakly relative" measures.[29]

Take China, for example. Chen and Ravallion (2021) studied the evolution of China's official poverty lines (which are only done for rural areas). The official poverty line fell from 64% of mean income in 1985 to 36% in 2011. Over the same period, the elasticity of the poverty line to the mean was 0.43. (The elasticity is higher for the more recent period, 2000-2011, for which the elasticity is 0.59.)

[27] For example, given the homogeneity property in equation (1), using *PovcalNet* one can readily simulate the impacts of any distribution-neutral growth process at the rate $g$ (increasing the mean by the factor $1+g$) by adjusting the poverty line downwards, i.e., using a new poverty line of $z/(1+g)$.
[28] Ravallion (2020) uses a dataset on implicit national lines produced by Jolliffe and Prydz (2017). Implicit national lines are estimated by numerically finding the quantile of reported national poverty rates.
[29] This idea also has an antecedent in Kakwani's work. In passing, Kakwani (1986) suggested a poverty line that rises linearly with mean income but has a positive intercept. This is also a weakly relative line. Chakravarty et al. (2015) provide an axiomatic derivation for a line of the form proposed by Kakwani.

Since this upward revision of the real value of national poverty lines is fairly common, there must be a reasonable presumption that weakly relative poverty measures are the norm, not the exception, and that they accord with evolving local perceptions of what "poverty" means. Naturally (holding all else constant), the growth elasticities of poverty reduction will be lower (less negative) for weakly relative poverty measures, though higher than for strongly relative measures; indeed, for strongly relative measures, the corresponding Kakwani elasticities (with respect to $\mu/z$ at given $\boldsymbol{L}$ in equation (1)) are automatically zero.

***Pro-poor growth?*** While the Kakwani elasticity holds (relative) distribution constant, another growth elasticity of poverty reduction is found in the literature, which lets the Lorenz curve shift consistently with the actual distributional changes (as in, for example, Ravallion 1995, and Ram 2011). As long as the poverty measure can be written in the form of equation (1) (in particular, that the Lorenz curve can be described by a vector of parameters), this elasticity can be written as:

$$\delta_P = \eta_P + \frac{\partial \ln P}{\partial \ln \boldsymbol{L}} . \frac{\partial \ln \boldsymbol{L}}{\partial \ln \mu} \tag{12}$$

(Here $\frac{\partial \ln P}{\partial \ln \boldsymbol{L}}$ is a log gradient vector, with $\frac{d \ln \boldsymbol{L}}{d \ln \mu}$ giving the corresponding vector of distributional changes.) The comparison of these two growth elasticities of poverty reduction has been used by Kakwani and Pernia (2000) to define a measure of "pro-poor growth," which one can write as $\delta_P/\eta_P$. By this definition, the actual growth process is said to be "pro-poor" if it reduces the poverty rate more than one would find with a distribution-neutral growth process.

An alternative definition of "pro-poor growth" says that growth is pro-poor if the agreed measure of poverty (which could be either absolute or relative) falls with that growth; following this second definition, one can measure the rate of pro-poor growth as the mean growth rate for those living below the poverty line (Ravallion and Chen 2003).

Take China, for example. In terms of absolute poverty reduction, it is widely agreed that China has seen a remarkable performance over the last 40 years or so. Since that reduction in poverty has come with rising inequality, it is not deemed "pro-poor" by the Kakwani-Pernia definition, though it is by the Ravallion-Chen definition. This is also true if one uses weakly relative poverty measures for China, whereby the real value of the poverty line rises with the mean, though with an elasticity less than unity (as in Chen and Ravallion 2021).

The relationship between these two definitions of pro-poor growth is especially clear if one uses the Watts index. Then the Ravallion-Chen measure of the rate of pro-poor growth is simply the Kakwani-Pernia definition times the actual rate of growth ($(\delta_W/\eta_W)\ d\ ln\,\mu$). For distribution-neutral growth, the Ravallion-Chen rate of pro-poor growth is simply the ordinary rate of growth. The rate of pro-poor growth can be positive even if it is not deemed to be "pro-poor" by the Kakwani-Pernia definition.

***Surveys versus national accounts:*** Yet a further issue that has emerged as important in practice is that growth in (say) GDP per capita ($Y$) need not be fully reflected in the growth rate of mean income or consumption derived from household surveys (Adams 2004; Ram 2011). There are many reasons why these two data sources need not agree, including differences in what is being measured and measurement errors, as discussed in Ravallion (2003) and Deaton (2005). If these differences can be treated as white noise then they will tend to attenuate regression-based estimates of the growth elasticity.

Based on Ravallion (2003), a reasonable assumption for the average elasticity of the survey mean to the corresponding national accounts aggregate is 0.75. For example, if one re-does my prior calculation that gave the average elasticity of -2.2 using growth rates of real GDP per capita instead of the growth rate from survey means then the slope of the regression line falls by about one quarter.[30] More precisely, I obtain a regression coefficient of -1.7 (with a standard error of 0.20). (Of course, as has already been emphasized, there is a sizeable variance in rates of poverty reduction at a given rate of growth, due to both measurement errors and systematic differences in the initial distributions and the growth processes.)

***Total growth elasticities:*** Combining these observations, and still keeping the analytic convenience of using the calculus, we can define the following total elasticity of poverty to growth in GDP per capita:

[30] The sources were *PovcalNet* and the *World Development Indicators*. For data reasons, the samples are somewhat smaller in this case (n=98).

$$\frac{d\ln P}{d\ln Y} = \left[\eta_P\left(1 - \frac{\partial \ln z}{\partial \ln \mu}\right) + \frac{\partial \ln P}{\partial \ln \boldsymbol{L}} . \frac{d \ln \boldsymbol{L}}{d\ln \mu}\right]\frac{\partial \ln \mu}{\partial \ln Y} \tag{13}$$

Recall that the average Kakwani elasticity for the headcount index is roughly -2. Continuing to assume (consistently with the data) that growth in the survey mean is distributional-neutral on average, and that the poverty line has an elasticity of 0.5 to the mean, the total elasticity is only about 40% of the Kakwani elasticity (more precisely, 0.5x0.75=0.375). That is a lot less poverty reduction from economic growth. And if you are talking about a high inequality country that Kakwani elasticity will need to be scaled down appreciably.

## 4. A Rawlsian perspective

It has come to be realized that the standard measures of poverty in the literature (including the distribution-sensitive measures) need not reflect well what is happening to the living standards of the poorest. One can have an unambiguous ranking of the distributions by every member of the class of additive poverty measures studied by Kakwani, for a very wide range of poverty lines, and yet find that nothing has happened to the level of living of the poorest. Yet, this can be seen as an important metric of social progress (following Rawls 1971). And social policy discussions (including in developing countries) often emphasize the need to lift the floor (Ravallion 2016a, b; Margitic and Ravallion 2019). The U.N.'s Sustainable Development Goals make frequent reference to the idea that development should "ensure no one is left behind" (UN, 2017); that requires that development lifts the floor.

We clearly need a lens with higher magnification, that tells us about the floor to living standards—below which their density is zero and above which it is positive. This cannot be reliably measured by the lowest observed consumption or income in a survey, which is likely to be a noisy indicator. Elsewhere I have proposed that, when using cross-sectional survey data, the floor should be estimated as the weighted mean consumption of those living below some level, with higher weight on people with lower observed consumption (Ravallion, 2016b). We can rationalize this by defining the floor as the expected value of the lower bound of an unobserved distribution of time-mean incomes, $y_i^*, i = 1, ... n$, given an observed distribution $\boldsymbol{y} \equiv (y_i, i = 1, \ldots, n)$. For the weighting scheme proposed by Ravallion (2016b), the expected value of the floor is given by:

$$y_\alpha^{min} \equiv E[min(y_i^*, i = 1, \dots n)|\boldsymbol{y}; \alpha) = \left(1 - \frac{P_{\alpha+1}}{P_\alpha}\right) z \tag{14}$$

While this is a function of FGT poverty measures, the interpretation of $z$ and $\alpha$ is different to that in Foster et al. (1984). In this context, $z$ is the income threshold above which there is no chance of being the poorest person while $\alpha$ is a curvature parameter in the probability function that gives the probability of any observed income level being the true lower bound to living standards (Ravallion 2016b). Comparing equations (5.1) and (14) and taking $z$ to be the poverty line, we see a relationship between the floor estimate above and the Kakwani elasticities, namely:

$$y_\alpha^{min} \equiv \left(\frac{\eta_{\alpha+1}}{\eta_{\alpha+1} - (\alpha+1)}\right) z \quad (\alpha > 0) \tag{15}$$

Similarly to the prior observation about differences in the depth of poverty, an implication of (15) is that distributions with lower (less negative) Kakwani elasticities will tend to have lower levels of their floor. In other words, countries where growth is less poverty reducing (by the Kakwani definition) will tend to be places where the poorest are worse off.

Using the Kakwani elasticities it can be shown that a necessary condition for $y_\alpha^{min}$ to grow at the same rate (or higher) as the overall mean is that the distribution of income improves from the perspective of poor people. Consider $y_1^{min} \equiv \left(1 - \frac{\text{SPG}}{\text{PG}}\right) z$. If all income levels grow at the same rate, leaving inequality unchanged, then (on noting that $\text{H} > \text{PG} > \text{SPG}$) we have:

$$\frac{\partial \ln y_1^{min}}{\partial \ln m} = 1 + \frac{\left(\frac{\text{PG}}{\text{H}} - \frac{\text{SPG}}{\text{PG}}\right)\text{H}}{\text{PG} - \text{SPG}} < 1 \tag{16}$$

In other words, with distribution-neutral growth and a fixed threshold (above which nobody can be the poorest), the poverty-weighted mean income of those below the threshold will tend to fall relative to the overall mean. In this sense, it can be said that the distribution will need to "improve" with growth to avoid the poorest being left behind. This property does not hold if the threshold is not fixed, but rises with the mean. For example, one can instead define the floor as the mean income of a fixed fractile, such as the poorest 20% (as discussed in Ravallion 2016b).

Empirically, the measure of the floor in (14) indicates only very modest growth in the floor of the distribution of permanent consumption in the world, which is still barely above a survival level (Ravallion, 2016b). In other words, for this “Rawlsian” measure of poverty, the growth elasticity has been close to zero for the developing world as a whole.

Faster progress in lifting the floor will almost certainly require that social policies are more effective in reaching the poorest. (This need not imply finer targeting; universal provision may well be the most effective way of lifting the floor.) Following this paper’s prior observations about the Kakwani elasticities, lifting the floor can be expected to enhance the effectiveness of even distribution-neutral economic growth in reducing poverty, since it will tend to raise the (absolute) elasticity to growth. Thus, we see a potential complementarity between policies that directly lift the floor and those that promote broader poverty-reduction through economic growth. Alas, we still appear to be a long way from fully exploiting that complementarity.

## 5. Conclusions

The Kakwani (1993) elasticities provide an insightful and easily understood analytical tool for linking economic growth and contraction, and changes in the extent of inequality, to standard measures of poverty. The calculation of these elasticities does not require parametric models or assumptions about the distributions of income or regression error terms. Once you makes Kakwani’s core assumptions, the formulae pop out straightforwardly from the math, and the required data are mostly nothing more than the measures of poverty one is calculating already. While economists are very comfortable using elasticities, economic literacy has probably constrained the number of applications of Kakwani’s elasticities over the last 30 years.

This paper has pointed to both strengths and weaknesses of the Kakwani elasticities, in the light of research since around the time Kakwani wrote his paper. In support of the use of these elasticities, growth in mean household consumption or income has been found to be roughly distribution-neutral on average, at least until recent times. This does not, of course, mean that inequality never changes; in fact, it changes a lot, and the changes can have substantial impacts on poverty measures (as Kakwani’s elasticities with respect to the Gini index illustrate). And we are starting to see inequality creeping up in many developing economies, which can greatly attenuate the impact of growth on poverty.

Nor is it true that national poverty lines in developing countries tend to have constant real value over time. This is not something that was much anticipated around 1990, since the large rise in average living standards we have seen in much of the developing world was yet to materialize. Poverty lines have tended to rise with the higher overall living standards. This alone could be expected to cut the Kakwani elasticity by roughly half on average.

A further reason why the growth elasticity of poverty reduction that we observe in practice can deviate from the Kakwani elasticity is that macroeconomic changes recorded in the national accounts do not always agree with what we see in household surveys. There has also been a discrepancy in the growth rates, with survey means falling relative to the closest measures found in the national accounts. This reflects differences in the concepts used and measurement errors in both data sources (including income under-reporting by the rich in surveys).

In my view, the value of the Kakwani elasticities lies in the insights they provide about the analytic properties of poverty measures rather than for decompositions, policy evaluations, or projections—all of which can be done without assuming constant elasticities, or even any explicit elasticities. The Kakwani elasticities vary over time, across countries, and with policy changes or shocks. Interestingly, the way they vary can imply scope for acceleration out of poverty, with (generally) rising elasticities as average income rises; or (equivalently) that less growth can assure the same rate of poverty reduction. By the same token, contracting economies will often face a greater handicap in restoring progress against poverty. Countries with a greater initial depth of poverty and/or greater inequality will also have a harder time reducing poverty through economic growth. Policies that lift the floor to living standards can help assure that future growth is more poverty reducing.

Since the 1980s, deeper explorations by economists of the analytic properties of measures of poverty and inequality—helped by greater access to, and use of, micro data—have enriched scholarly discussion and helped inform policy debates. An economist writing something like Kakwani's (1993) paper today would probably make somewhat different assumptions, reflecting how things have changed. We no longer live in a world where either distribution-neutrality or Lorenz dominance, or even absolute poverty measures, can be considered plausible. However, as an early formative example of this analytic approach, Kakwani's paper can be considered a landmark in the history of thought on poverty and inequality.

## References

Adams, Richard, 2004, "Economic Growth, Inequality and Poverty: Estimating the Growth Elasticity of Poverty." *World Development* 32(12): 1989–2014.

Arndt, Channing, Kristi Mahrt, Caroline Schimanski, 2017, "On the Poverty-Growth Elasticity," WIDER Working Paper, No. 2017/149, ISBN 978-92-9256-375-2, The United Nations University World Institute for Development Economics Research (UNU-WIDER), Helsinki.

Atkinson, Anthony B., 1987, "On the Measurement of Poverty," *Econometrica* 55: 749-764.

Berardi, Nicoletta, and Federica Marzo, 2017, "The Elasticity of Poverty with Respect to Sectoral Growth in Africa," *Review of Income and Wealth* 63(1): 147-168.

Bergstrom, Katy, 2020, "The Role of Inequality for Poverty Reduction," Policy Research Working Paper 9409, World Bank, Washington DC.

Besley, Timothy, and Ravi Kanbur, 1988, "Food Subsidies and Poverty Reduction," *Economic Journal* 98: 701-719.

Bourguignon, François, 2003, "The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity across Countries and Time Periods," in T. Eicher and S. Turnovsky (eds) *Inequality and Growth: Theory and Policy Implications*, Cambridge: MIT Press.

___________________, 2004, "The Poverty-Growth-Inequality Triangle," Working Paper, No. 125, Indian Council for Research on International Economic Relations (ICRIER), New Delhi.

Bresson, Florent, 2009, "On the Estimation of Growth and Inequality Elasticities of Poverty with Grouped Data," *Review of Income and Wealth* 55(2): 266-302.

Chakrangi Lenagala, and Rati Ram, 2010, "Growth Elasticity of Poverty: Estimates from New Data," *International Journal of Social Economics* 37(12): 923-932.

Chakravarty S, N. Chattopadhyay, Z. Nissanov, and J. Silber, 2015, "Reference Groups and the Poverty Line: An Axiomatic Approach with an Empirical Illustration," WIDER WP 2015/002.

Chen, Shaohua, and Martin Ravallion, 2010, "The Developing World is Poorer than we Thought, but no Less Successful in the Fight against Poverty," *Quarterly Journal of Economics*, 125(4): 1577-1625.

_____________, and _____________, 2021, "Reconciling the Conflicting Narratives on Poverty in China," *Journal of Development Economics*, in press.

Collier, Paul, and David Dollar, 2002, "Aid Allocation and Poverty Reduction," *European Economic Review* 46(8): 1475–1500.

Datt, Gaurav and Martin Ravallion. 1992. "Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Applications to Brazil and India in the 1980s." *Journal of Development Economics* 38: 275-295.

Datt, Gaurav, Martin Ravallion and Rinku Murgai, 2020, "Poverty and Growth in India over Six Decades," *American Journal of Agricultural Economics* 102(1): 4-27.

Deaton, Angus, 2005, "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *Review of Economics and Statistics* 87(1): 1-19.

De Vreyer, Philippe, and Sylvie Lambert, 2021, "Inequality, Poverty and the Intra-household Allocation of Consumption in Senegal," *World Bank Economic Review* 35(2): 414-435.

Dollar, David, and Kraay, Aart, 2002, "Growth is Good for the Poor," *Journal of Economic Growth* 7(3): 195-225.

Ferreira, Francisco, and Martin Ravallion, 2009, "Poverty and Inequality: The Global Context," in *The Oxford Handbook of Economic Inequality*, edited by Wiemer Salverda, Brian Nolan and Tim Smeeding, Oxford: Oxford University Press.

Foster, James, Joel Greer, and Erik Thorbecke, 1984, "A Class of Decomposable Poverty Measures," *Econometrica* 52: 761-765.

Fosu, Augustin Kwasi, 2017, "Growth, Inequality, and Poverty Reduction in Developing Countries: Recent Global Evidence," *Research in Economics* 71(2): 316-336.

Haddad, Lawrence, and Ravi Kanbur, 1990, "How Serious is the Neglect of Intra-Household Inequality?," *Economic Journal* 100: 866-881.

Heltberg, Rasmus, 2004, "The Growth Elasticity of Poverty," in A. Shorrocks and R. van der Hoeven (eds) *Growth, Inequality and Poverty*. Oxford: Oxford University Press.

Jolliffe Dean, and Esben Prydz, 2017. "Global Societal Poverty: a Relative and Relevant Measure," Policy Research Working Paper 8073, World Bank.

Kakwani, Nanak, 1986. *Analyzing Redistribution Policies: A Study using Australian Data.* Cambridge: Cambridge University Press.

______________, 1990, "Poverty and Economic Growth with Applications to Côte D'Ivoire." World Bank Living Standards Measurement Study, Working Paper 63. Washington, D.C.

______________, 1993, "Poverty and Economic Growth with Application to Côte D'Ivoire," *Review of Income and Wealth* 39(2): 121-139.

Kakwani, Nanak, and Ernesto Pernia, 2000, "What is Pro-Poor Growth?" *Asian Development Review* 16(1): 1–22.

Kanbur, Ravi, 1987, "Measurement and Alleviation of Poverty," *IMF Staff Papers* 36: 60-85.

Klasen, Stephan, and Mark Misselhorn, 2008, "Determinants of the Growth Semi-elasticity of Poverty Reduction," Ibero America Institute for Economic Research Discussion Paper 176. Göttingen: Georg-August-Universität Göttingen.

Kraay, Aart, 2006, "When is Growth Pro-poor? Evidence from a Panel of Countries," *Journal of Development Economics* 80: 198–227.

Lakner, Christoph, and Branko Milanovic, 2016, "Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession," *World Bank Economic Review* 30(2): 203-232.

Lipton, Michael, and Martin Ravallion, 1995, "Poverty and Policy," in Jere Behrman and T.N. Srinivasan (eds) *Handbook of Development Economics, Volume 3,* Amsterdam: North-Holland.

Loayza, Norman, Raddatz, Claudio, 2010, "The Composition of Growth Matters for Poverty Alleviation," *Journal of Development Economics* 93(1): 137-151.

Margitic Juan, and Martin Ravallion, 2019, "Lifting the floor? Economic Development, Social Protection and the Developing World's Poorest," *Journal of Development Economics* 139(June): 97-108.

McKay, Andrew, 2007, "Introduction to Methods for Analyzing the Distributional Pattern of Growth," in Michael Grimm, Stephen Klasen and Andrew McKay (eds), *Determinants of Pro-Poor Growth*, New York: Palgrave Macmillan.

Montalvo, Jose, and Martin Ravallion, 2010, "The Pattern of Growth and Poverty Reduction in China," *Journal of Comparative Economics* 38: 2-16.

Ram, Rati, 2011, "Growth Elasticity of Poverty: Direct Estimates from Recent Data," *Applied Economics* 43(19): 2433–440.

Ravallion, Martin, 1995, "Growth and Poverty: Evidence for Developing Countries in the 1980s," *Economics Letters* 48: 411-417.

_______________, 1997, "Can High Inequality Developing Countries Escape Absolute Poverty?" *Economics Letters* 56: 51-57.

_______________, 2001, "Growth, Inequality and Poverty: Looking Beyond Averages." *World Development* 29(11): 1803-1815.

_______________, 2003, "Measuring Aggregate Economic Welfare in Developing Countries: How Well do National Accounts and Surveys Agree?" *Review of Economics and Statistics* 85: 645–652.

_______________, 2005, "A Poverty-Inequality Trade-Off?" *Journal of Economic Inequality* 3(2): 169-182.

_______________, 2007, "Inequality is Bad for the Poor," in J. Micklewright and S. Jenkins (eds.), *Inequality and Poverty Re-Examined.* Oxford: Oxford University Press.

_______________, 2011, "A Comparative Perspective on Poverty Reduction in Brazil, China and India," *World Bank Research Observer* 26(1): 71-104.

_______________, 2012, "Why Don't we See Poverty Convergence?" *American Economic Review*, 102(1): 504-523.

_______________, 2016a, *Economics of Poverty: History, Measurement and Policy*. New York: Oxford University Press.

_______________, 2016b, "Are the World's Poorest Being Left Behind?" *Journal of Economic Growth* 21(2): 139–164.

_______________, 2018, "Inequality and Globalization: A Review Essay," *Journal of Economic Literature* 56(2): 1-23.

_______________, 2020, "On Measuring Global Poverty," *Annual Review of Economics* 12: 167-188.

_______________, 2021a, "What Might Explain Today's Conflicting Narratives on Global Inequality?" in Carlos Gradín, Murray Leibbrandt, and Finn Tarp (eds) *Inequality in the Developing World*. Oxford: Oxford University Press.

________________, 2021b, "Missing Top Income Recipients," NBER Working Paper 28890. (*Journal of Economic Inequality*, forthcoming).

Ravallion, Martin, and Shaohua Chen, 2003, "Measuring Pro-Poor Growth," *Economics Letters* 78(1): 93-99.

______________, and ____________, 2007, “China’s (Uneven) Progress Against Poverty.” *Journal of Development Economics* 82(1): 1-42.

______________, and ____________, 2011, “Weakly Relative Poverty,” *Review of Economics and Statistics* 93(4): 1251-1261.

Ravallion, Martin and Gaurav Datt, 1996, “How Important to India's Poor is the Sectoral Composition of Economic Growth?”, *World Bank Economic Review* 10: 1-26.

Ravallion, Martin, Gaurav Datt, and Dominique van de Walle, 1991, “Quantifying Absolute Poverty in the Developing World,” *Review of Income and Wealth* 37: 345-361.

Ravallion Martin, and Monika Huppi, 1991, “Measuring Changes in Poverty: A Methodological Case Study of Indonesia during an Adjustment Period,” *World Bank Economic Review* 5(1): 57- 82.

Rawls, John, 1971, *A Theory of Justice*, Cambridge MA: Harvard University Press.

Sen, Amartya, 1976, “Poverty: An Ordinal Approach to Measurement,” *Econometrica* 46: 437-446.

Son, Hyun H. and Nanak Kakwani, 2004, “Economic Growth and Poverty Reduction: Initial Conditions Matter,” Working Paper 2, International Poverty Centre, UNDP.

United Nations, 2017, *The Sustainable Development Goals Report*, New York: United Nations.

Watts, Harold W., 1968, “An Economic Definition of Poverty,” in Daniel P. Moynihan (ed.), *On Understanding Poverty*, New York, Basic Books.

Wieser, Christina, 2011, “Determinants of the Growth Elasticity of Poverty Reduction Why the Impact on Poverty Reduction is Large in Some Developing Countries and Small in Others,” WIFO Working Paper 406.

World Bank, 1990, *World Development Report: Poverty*. New York: Oxford University Press.

__________, 2016. *Global Monitoring Report 2015/2016: Development Goals in an Era of Demographic Change*. Washington, D.C.

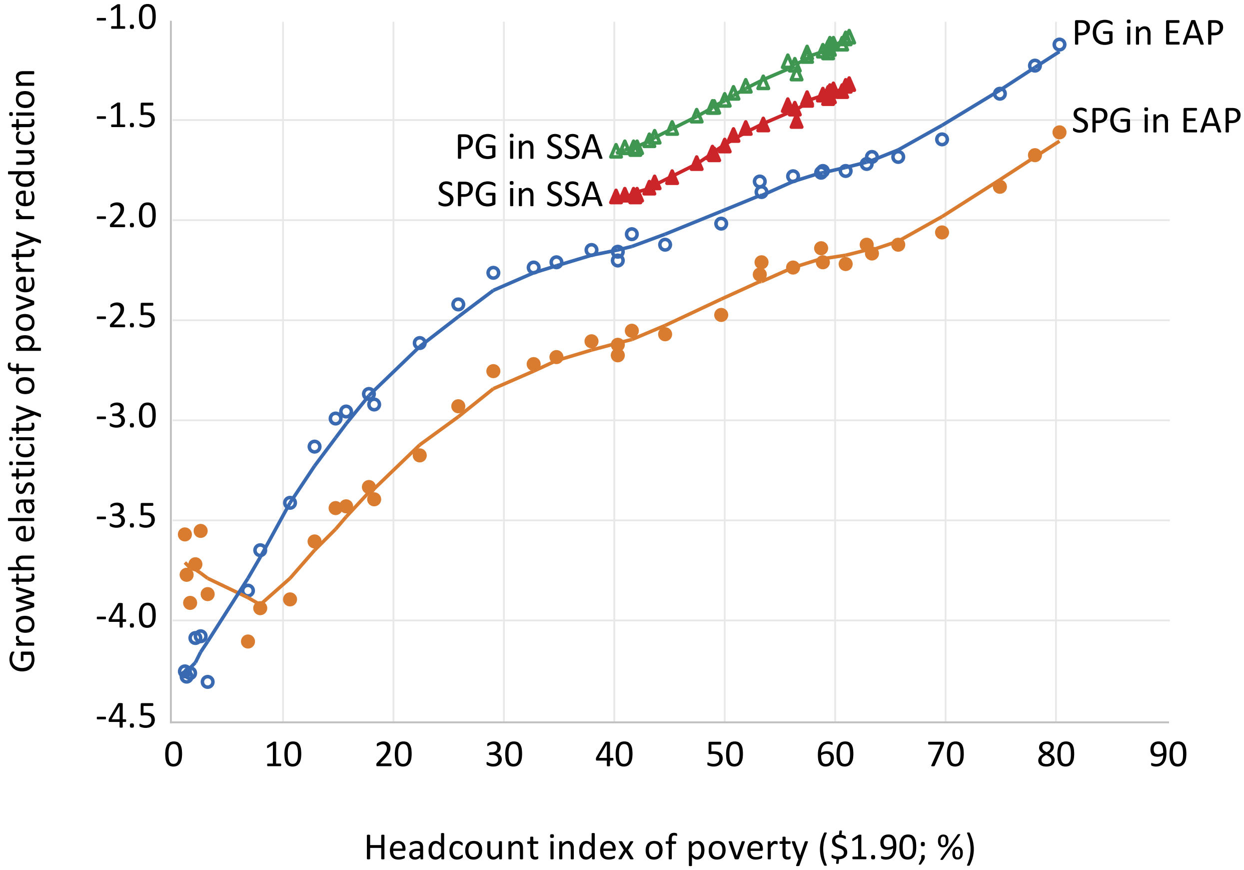
**Table 1: FGT poverty measures and Kakwani elasticities by region for selected years**

| | Region | Poverty measure (x100) | | | Kakwani elasticity ($\eta_\alpha$) | |
|---|---|---|---|---|---|---|
| | | H | PG | SPG | PG | SPG |
| 2018 | EAP | 1.18 | 0.22 | 0.08 | -4.26 | -3.57 |
| 2018 | ECA | 1.13 | 0.34 | 0.16 | -2.37 | -2.18 |
| 2018 | LAC | 3.80 | 1.34 | 0.71 | -1.85 | -1.78 |
| 2018 | MNA | 7.22 | 2.07 | 0.86 | -2.49 | -2.82 |
| 2018 | SAS | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2018 | SSA | 40.19 | 15.14 | 7.79 | -1.65 | -1.89 |
| 2018 | WLD | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2014 | EAP | 2.63 | 0.52 | 0.19 | -4.09 | -3.55 |
| 2014 | ECA | 1.79 | 0.54 | 0.27 | -2.29 | -2.03 |
| 2014 | LAC | 4.13 | 1.50 | 0.89 | -1.76 | -1.37 |
| 2014 | MNA | 2.70 | 0.55 | 0.18 | -3.94 | -3.95 |
| 2014 | SAS | 15.19 | 2.83 | 0.81 | -4.37 | -5.02 |
| 2014 | SSA | 42.10 | 15.96 | 8.24 | -1.64 | -1.88 |
| 2014 | WLD | 10.67 | 3.20 | 1.50 | -2.33 | -2.27 |
| 2010 | EAP | 10.74 | 2.43 | 0.82 | -3.41 | -3.90 |
| 2010 | ECA | 2.38 | 0.66 | 0.29 | -2.63 | -2.60 |
| 2010 | LAC | 6.23 | 2.56 | 1.57 | -1.44 | -1.27 |
| 2010 | MNA | 2.06 | 0.38 | 0.13 | -4.42 | -4.02 |
| 2010 | SAS | 25.95 | 5.61 | 1.80 | -3.62 | -4.24 |
| 2010 | SSA | 47.47 | 19.13 | 10.29 | -1.48 | -1.72 |
| 2010 | WLD | 16.02 | 4.76 | 2.16 | -2.36 | -2.40 |
| 2005 | EAP | 18.27 | 4.66 | 1.73 | -2.92 | -3.40 |
| 2005 | ECA | 4.70 | 1.37 | 0.60 | -2.43 | -2.61 |
| 2005 | LAC | 10.02 | 4.12 | 2.50 | -1.43 | -1.30 |
| 2005 | MNA | 3.16 | 0.55 | 0.16 | -4.75 | -4.71 |
| 2005 | SAS | 34.88 | 8.28 | 2.82 | -3.21 | -3.88 |
| 2005 | SSA | 51.97 | 22.27 | 12.59 | -1.33 | -1.54 |
| 2005 | WLD | 20.93 | 6.42 | 2.94 | -2.26 | -2.36 |
| 2000 | EAP | 34.79 | 10.83 | 4.62 | -2.21 | -2.68 |
| 2000 | ECA | 7.29 | 2.23 | 1.00 | -2.27 | -2.45 |
| 2000 | LAC | 12.76 | 5.61 | 3.63 | -1.27 | -1.10 |
| 2000 | MNA | 3.74 | 0.70 | 0.22 | -4.32 | -4.27 |
| 2000 | SAS | | | | | |
| 2000 | SSA | 58.94 | 27.33 | 16.20 | -1.16 | -1.37 |
| 2000 | WLD | 27.72 | 9.21 | 4.39 | -2.01 | -2.20 |
| 1995 | EAP | 44.68 | 14.33 | 6.27 | -2.12 | -2.57 |
| 1995 | ECA | 6.71 | 2.12 | 1.08 | -2.16 | -1.94 |
| 1995 | LAC | 12.64 | 5.25 | 3.26 | -1.41 | -1.22 |
| 1995 | MNA | 6.80 | 1.26 | 0.39 | -4.38 | -4.47 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1995 | SAS | 43.45 | 11.35 | 4.17 | -2.83 | -3.44 |
| 1995 | SSA | 60.93 | 29.13 | 17.51 | -1.09 | -1.33 |
| 1995 | WLD | 31.29 | 10.53 | 5.03 | -1.97 | -2.19 |
| 1990 | EAP | 60.85 | 22.14 | 10.50 | -1.75 | -2.22 |
| 1990 | ECA | 3.12 | 0.90 | 0.48 | -2.48 | -1.76 |
| 1990 | LAC | 15.15 | 6.24 | 3.72 | -1.43 | -1.35 |
| 1990 | MNA | 6.59 | 1.26 | 0.41 | -4.24 | -4.10 |
| 1990 | SAS | 48.69 | 13.85 | 5.40 | -2.52 | -3.13 |
| 1990 | SSA | 55.71 | 25.29 | 14.78 | -1.20 | -1.42 |
| 1990 | WLD | 36.22 | 12.84 | 6.18 | -1.82 | -2.15 |

Note: Poverty line=$1.90 per day at 2011 PPP. EAP: East Asia and Pacific; ECA: Eastern and Central Asia; LAC: Latin America and the Caribbean; MNA: Middle East and North Africa; SAS: South Asia; SSA: Sub-Saharan Africa; WLD: World (incl. high-income countries). Note that the fact that the Government of India has not released its poverty data from the latest National Sample Survey means that estimates are not included for SAS in 2018.
Source: Author's calculations using data from *PovcalNet*.

**Figure 1: Kakwani growth elasticities for East Asia (EAP) and Sub-Saharan Africa (SSA)**




Note: PG is the poverty gap index, and SPG is the squared poverty gap index.
Source: Author's calculations using data from *PovcalNet*.