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THE PRO-POORNESS, GROWTH AND INEQUALITY NEXUS: SOME FINDINGS FROM A SIMULATION STUDY

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An income growth pattern is pro-poor if it reduces a (chosen) measure of poverty by *more* than if all incomes were growing equiproportionately. Inequality reduction is not sufficient for pro-poorness. In this paper, we explore the nexus between pro-poorness, growth, and inequality in some detail using simulations involving the displaced lognormal, Singh–Maddala, and Dagum distributions. For empirically relevant parameter estimates, distributional change preserving the functional form of each of these three-parameter distributions is often either pro-poor and inequality reducing, or pro-rich and inequality exacerbating, but it is also possible for pro-rich growth to be inequality reducing. There is some capacity for each of these distributions to show trickle effects (weak pro-richness) along with inequality-reducing growth, but virtually no possibility of pro-poorness for growth which increases overall inequality. Implications are considered.

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1. INTRODUCTION

Pro-poor (or "inclusive") growth is defined as growth which reduces poverty by more than would a benchmark growth pattern, and this benchmark may be normatively set (Osmani, 2005; Jayaraj and Subramanian, 2012). Taking the benchmark growth pattern to be equiproportionate or distributionally neutral, we arrive at Kakwani and Pernia's (2000) concept and measure of pro-poorness or inclusivity. Pro-poor growth according to this criterion, being focused more toward the poor than inequality-neutral growth, should intuitively be inequality-reducing, but this may not go the other way: growth spells which are inequality-reducing may not be pro-poor, and growth spells which are not pro-poor (typically called "pro-rich") may nonetheless be inequality reducing. In this Note we explore and illustrate the possibilities for pro-poorness/richness and inequality reduction/

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exacerbation when growth takes place within the displaced lognormal, Singh–Maddala, and Dagum income distributions.

Recourse to a three-parameter distributional form to explore such effects seems necessary because of a finding for the lognormal distribution, which has only two parameters. Smolensky *et al*. (1994, p. 217) observe that "The assumption of a lognormal distribution . . . explains the time path of poverty [in the U.S. in the 1970s and 1980s] reasonably well." But for growth taking place within the lognormal distribution, whether expansionary or contractionary, distributional change is unambiguously pro-poor if inequality falls and unambiguously pro-rich if inequality rises.[1] This result is very strong: it holds for any index of relative inequality, for all members of the additive and separable class of poverty indices, and for any chosen and fixed poverty line. The result arises because the lognormal spread parameter is perforce doing double-duty in determining both inequality and pro-poorness effects; one cannot model incomes as lognormal to replicate scenarios, present in the real world, where pro-poorness comes with increased inequality, and conversely where pro-richness is associated with inequality reduction.

These less than intuitive associations do indeed occur in practice. Just consider Jayaraj and Subramanian's (2012) finding, using Indian consumption expenditure data for the period from 1970/71 to 2009/10, that across the nine year-on-year growth experiences involved, the inequality effect in terms of the Gini coefficient is variable (rising in three cases for the rural population and in five for the urban) – but that uniformly across all cases, and for a range of inclusiveness concepts which these authors explored, "the record of growth . . . has been . . . exclusionary rather than . . . pro-poor" (p. 20).[2]

The structure of the paper is as follows. In Section 2, we briefly specify relevant details of the parametric forms for the income distributions with which we are concerned. In Section 3, the framework for pro-poorness measurement is sketched. Section 4 contains our findings in respect of pro-poorness and inequality reduction for income growth patterns which preserve the assumed form of the income distribution, when inequality is measured by the Gini coefficient and poverty by the Watts index. Section 5 discusses robustness issues, and Section 6 concludes.

2. The Distributions

Each of the displaced lognormal, Singh–Maddala, and Dagum distributions has three parameters, and is defined, described, and analyzed in Kleiber and Kotz (2003).

[1]This result is predicated on society being non-destitute, i.e. on the poverty line being below the mean income value. See Lambert (2010).

[2]Other studies can also be cited, though the definition of pro-poorness varies across them. Ravallion (2001) finds "no sign that distributional changes help protect the poor during contractions" (p. 1806), but also that "during spells of growth or contraction one sees changes in inequality . . . in both directions" (p. 1808 and table 1). In Son and Kakwani's (2008) analysis, covering 237 growth spells in 80 countries during the period 1984–2001, 44.7 percent were contractions, of which about half were pro-poor, as were just over one third of the expansions (see especially p. 1050 and table 1). We shall return to the inequality and pro-poorness measures used in Son and Kakwani's study toward the end of our paper.

The displaced lognormal corrects for the negative skewness which is typically found in the distribution of log income and, although not very common in empirical work, it has for example been used by Gottschalk and Danziger (1985) to model income divided by the poverty line in a study of U.S. growth and poverty, and by Alexeev and Gaddy (1992) to model per capita income distribution in the USSR in the 1980s. Letting x be income and letting k, θ, σ be the three parameters, such that $\ell n(x - k) \sim N(\theta, \sigma^2)$, a typical income may be generated as $x = k + \exp(\theta + u\sigma)$ where $u \sim N(0, 1)$. The Gottschalk and Danziger parameter estimates for 1982 are $\{k, \theta, \sigma\} = \{1.2, 2.8, 6.0\}$ whilst the Alexeev and Gaddy estimates for Russia are $\{k, \theta, \sigma\} = \{14.8, 4.98, 0.56\}$ for 1990.

The Singh–Maddala distribution was found by McDonald (1984) to provide a better fit to U.S. family nominal income for 1970–80 than any other 2- or 3-parameter distribution he tried, and also better than some 4-parameter distributions. With positive parameter values a, b and q, incomes can be generated as $x = b\left[(1-u)^{-1/q} - 1\right]^{1/a}$ where u is uniformly distributed on [0,1]. The parameter estimates given in McDonald and Mantrala (1995) for the U.S. in 1990 are $\{a, b, q\} = \{1.6, 125, 5.3\}$.

The Dagum distribution is held by its supporters to provide a better fit yet than the Singh–Maddala (see, e.g., Kleiber and Kotz, 2003, pp. 221–22). With positive parameter values a, b and p, incomes can be generated as $x = b(u^{-1/p} - 1)^{-1/a}$ where u is uniformly distributed on [0, 1]. The parameter estimates reported by McDonald and Mantrala (1995) for the U.S. in 1990 are $\{a, b, p\} = \{3.3, 66, 0.43\}$.

3. Measurement Issues

Let the frequency density function for incomes be $f(x|s_1, s_2, s_3)$ in the base period, and let the cumulative distribution function be $F(x|s_1, s_2, s_3)$. Inequality and poverty indices can be expressed in terms of f and F, the latter requiring specification of a poverty line. Throughout this paper we shall assume a fixed poverty line, equal in fact to 50 percent of the base median income value, and this is not varied when the parameters (s_1, s_2, s_3) are changed.[3]

When the parameters are varied, $(s_1, s_2, s_3) \to (s_1 + ds_1, s_2 + ds_2, s_3 + ds_3)$ say, for $0 < p < 1$ let $F(x(p)|s_1, s_2, s_3) = p = F(x(p) + dx(p)|s_1 + ds_1, s_2 + ds_2, s_3 + ds_3)$, that is, we track the effect of growth on each quantile rather than on each individual.[4] Define $q(x(p)) = [dx(p)/x(p) \div d\mu/\mu]$, where μ is the mean base income. This is an

[3]Hence we are concerned with absolute poverty but, as will emerge, with relative inequality. These concepts are ubiquitous in the development context, where poverty lines are typically fixed in real income terms. We choose the poverty line z to be 50 percent of the median for illustrative purposes only. The poverty line used by the Statistical Office of the European Commission (Eurostat) is 60 percent of median income. This percentage is also used in the *Households Below Average Income* publications of the UK's Department for Work and Pensions. Later in the paper, we explore the sensitivity of our results to the level of the poverty line, inter alia.

[4]New issues must be confronted to track individual rather than quantile poverty experiences, if some who are initially poor, as well as some who are not, cross the poverty line during growth (see Grimm, 2007). With panel data, one can of course track individual experiences, and would not then need or want to fit a functional form to the anonymised base and post-growth income distributions, as here.

elasticity function characterizing the growth pattern. Ravallion and Chen's (2003) growth incidence curve at percentile p is $GIC(p) = dx(p)/x(p)$.[5]

For the Kakwani and Pernia measure of pro-poorness with poverty index P, pro-poorness for the growth pattern $q(.)$ takes the form $\kappa(q) = \frac{-\Delta P}{-\Delta_0 P}$ for expansionary growth and $\kappa(q) = \frac{\Delta_0 P}{\Delta P}$ (the reciprocal) for contractionary growth, where ΔP signifies the change in poverty under $q(.)$ whilst $\Delta_0 P$ signifies the change that would take place were growth equiproportionate at the same rate. Thus for expansionary growth, $\kappa(q)$ measures the decrease in poverty for growth pattern $q(.)$ relative to the counterfactual decrease for equiproportionate growth, whilst for contractionary growth (recession), $\kappa(q)$ measures the rise in poverty for equiproportionate growth at the same overall rate as a multiple of the rise for the actual growth pattern $q(x)$. In either case, pro-poorness occurs when $\kappa(q) > 1$. Pro-poorness measurement is systematized in terms of the elasticity function $q(.)$ by Essama-Nssah and Lambert (2009), where formulae for $\kappa(q)$ are given for various poverty indices P, including the Watts index, in terms of $q(.)$ and the base income density function.[6] Pro-richness occurs when $\kappa(q) < 1$. For expansionary growth, $0 < \kappa(q) < 1$ indicates benefits to the poor which are weakly less than to the rich, a situation characterized by Kakwani and Pernia (2000) as "trickle-down" growth. For recession, we could say that $0 < \kappa(q) < 1$ indicates "trickle-up," because the losses to the poor are weakly more than those to the rich.

4. Our Simulation Findings

Using the base values for (s_1, s_2, s_3) already cited (in the displaced lognormal case, we use the Russian values, so that all estimates are for 1990), and a poverty line equal to 50 percent of median base income, we chose 20 small changes for each parameter, using values $\Delta s_1 = \pm 0.5, \pm 1.0, \pm 1.5, \ldots \pm 5.0$ for the displaced lognormal, $\Delta s_1 = \pm 0.01, \pm 0.02, \pm 0.03, \ldots \pm 0.10$ for the Singh–Maddala and Dagum; $\Delta s_2 = \pm 0.01, \pm 0.02, \pm 0.03, \ldots \pm 0.10$ for the displaced lognormal, $\Delta s_2 = \pm 1, \pm 2, \pm 3, \ldots \pm 10$ for the Singh–Maddala, and $\Delta s_2 = \pm 0.5, \pm 1, \pm 1.5, \ldots \pm 5.0$ for the Dagum; and $\Delta s_3 = \pm 0.01, \pm 0.02, \pm 0.03, \ldots \pm 0.10$ in all three cases. We calculated the Gini coefficient G and the pro-poorness measure $\kappa(q)$ for the Watts index in each constellation. In this way, we obtained in fact 9,261 values for the proportional inequality effect $\frac{\Delta G}{G}$ and the pro-poorness measure $\kappa(q)$ as the income growth pattern $q(\cdot)$ varied within each distribution (including changes of zero associated with the initial values of the parameters). Our findings are summarized in Figures 1–3, on a common "template" with marked sectors: IR/IE means inequality reducing/inequality enhancing, PP/PR means pro-poor/pro-rich, and Trickle denotes weak pro-richness. These figures

[5]See Grimm (2007) and also Bourguignon (2011) on adapting the growth incidence curve to the tracking of individual rather than quantile growth experiences.

[6]As a referee pointed out, growth, changes in poverty and changes in inequality are in essence different aggregations of the information contained in a growth incidence curve.

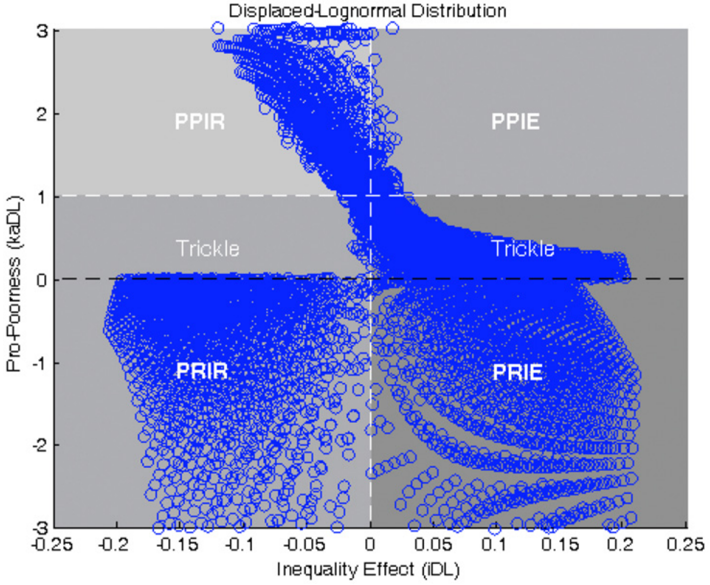

Figure 1. Displaced Lognormal $\left(\frac{\Delta G}{G}, \kappa(q)\right)$ Scattergram

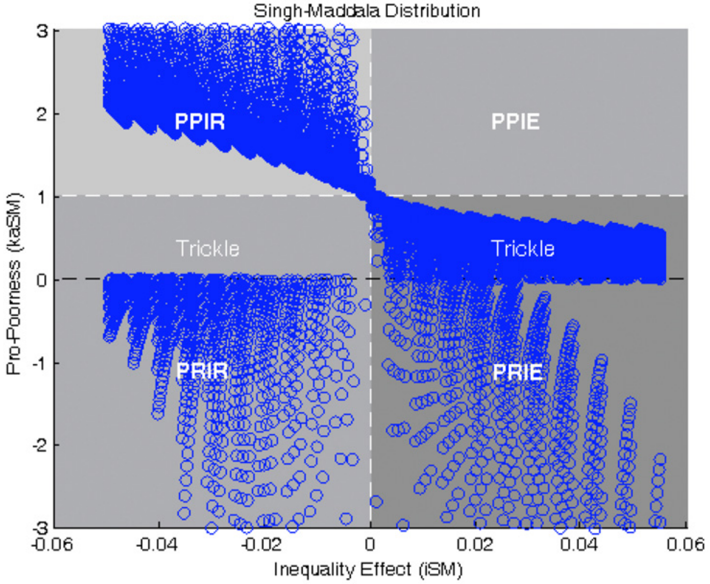

Figure 2. Singh–Maddala $\left(\frac{\Delta G}{G}, \kappa(q)\right)$ Scattergram

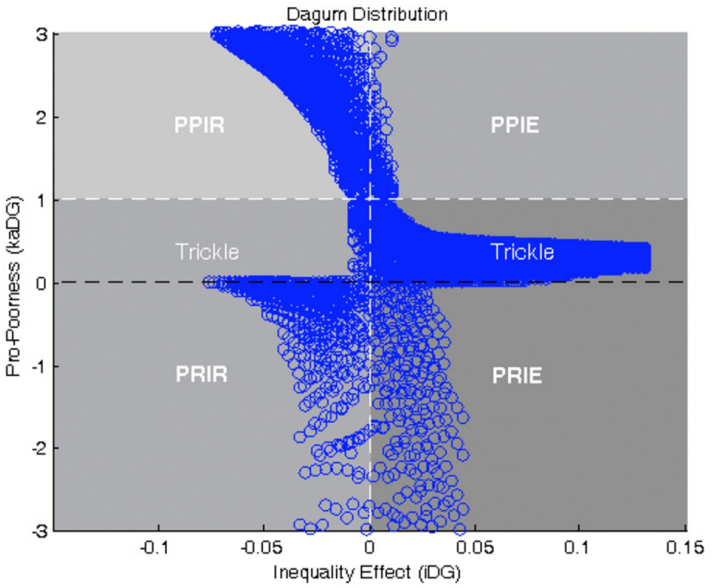

Figure 3. Dagum $\left(\frac{\Delta G}{G}, \kappa(q)\right)$ Scattergram

display, for parameter changes which increase (decrease) the mean, which of them reduce inequality, and which of them reduce poverty by more (raise poverty by less) than would benchmark income change.

For the displaced lognormal distribution, we see that the PPIR quadrant is well-populated, and that, strikingly, the PPIE quadrant is almost empty. In essence, then, pro-poor change is inequality reducing—as we suggested would be the case on intuitive grounds at the outset—but this does not go the other way, as both the PRIR and PRIE quadrants are quite densely populated: pro-rich change preserving the displaced lognormal form can occur concomitantly with either inequality reduction or inequality exacerbation. There is little capacity for a trickle effect if growth is inequality-reducing. For the Singh–Maddala distribution, our findings are qualitatively similar, with the PPIE sector also being virtually empty; in this case, trickle hardly occurs for inequality-reducing growth. For the Dagum distribution, again the PPIE sector is almost empty, and the regions of strong pro-rich change occurring both with inequality reduction and with inequality exacerbation are quite confined.

In summary, for these three distributions, and using the cited parameter estimates for Russia and the U.S. in 1990, distributional change is often either pro-poor and inequality reducing, or pro-rich and inequality exacerbating, but not always. There is almost no capacity for growth to display pro-poorness and an inequality increase (we return to this point in our Conclusions). There is thin evidence of trickle when inequality is reduced; weak pro-richness comes, in the main, only in conjunction with inequality exacerbation.

Although for each distribution there are three parameters, and there are three indicators of distributional change—growth, pro-poorness, and the inequality effect—it is difficult to divine which parameter may be the most influential one in driving, say, the pro-poorness measure, or the inequality change. We were able to make some headway in Groll and Lambert (2011) for the displaced lognormal, by reparameterizing, but the technical details are omitted here.[7] We could see no patterns at work in the case of the Singh–Maddala and Dagum distributions, but this could be a fruitful line for future exploration.[8]

5. Robustness

Our findings may, of course, be particular to our choices, (i) of initial parameter values, (ii) of (fixed) poverty line, (iii) of the Watts index to measure poverty, and (iv) of the Gini coefficient to measure inequality. We comment on these in turn:[9] (i) in Bandourian *et al.* (2003), Singh–Maddala, and Dagum distributions are fitted to data from 23 countries spanning 30 years, 81 regimes in all, and for a selection of the cited parameter estimates, we found the graphical depictions to be very similar the ones we have displayed; (ii) although we had chosen to use 50 percent of the base median income as poverty line, we repeated our simulations using 40 and 60 percent of the base median, and got results which are very similar; (iii) we repeated the entire analysis for the well-known FGT(2) poverty index (squared poverty gap), and found very similar graphical depictions to those in Figures 1–3; and (iv) we also redid the simulations using the coefficient of variation as inequality measure, and again found very similar graphical depictions (using either the Watts or the FGT(2) poverty index).[10]

As a final point, we mention that a non-standard pro-poorness measure and associated inequality index introduced by Son and Kakwani (2008), if adopted here, would reduce our scatterplots for all three distributions – and any other – to 45° downward sloping straight lines through the origin.[11] In particular, if growth were such that the associated measure of inequality did not change, there would

[7]Specifically, we showed that the signs of $d\sigma$, $d\theta + \sigma d\sigma$ and dk can be used to determine a priori (independent of magnitudes) some scenarios in which pro-poorness or pro-richness can be determined and definitively linked with the inequality effect of the distributional change, although the parameter values/signs which lead to this conclusion are quite particular (see Groll and Lambert, 2011, pp. 9–10 and appendix).

[8]Recall that the scatter points in our figures are generated by simultaneous changes in all three parameters. For each of the Singh–Maddala and Dagum distributions, one can associate specific parameters with shape properties of the density functions, and there are alternative parameterizations which might be worthy of exploration. See Kleiber and Kotz (2003, pp. 198–214).

[9]Recall that the relative inequality and absolute poverty concepts are at the heart of this study. To explore robustness of our findings to changes in these concepts, or to a change in the benchmark growth pattern from that of distribution neutrality, would be beyond the scope of the paper.

[10]All of these scatterplots are available from the authors on request. The only case we explored which produced somewhat dissimilar findings was when using the headcount ratio as poverty index. In this case, the scatters covered the PPIR and PRIE quadrants thickly, and overlapped the PPIR and PRIE quadrants significantly, with negative correlations. But growth for this poverty index need only reduce the number of poor by more than under inequality–neutrality for it to count as pro-poor. The intuition we have suggested, linking pro-poorness with inequality reduction, founders somewhat for this distribution-insensitive poverty index.

[11]Son and Kakwani develop two alternative "pro-poor growth rate" measures, each of whose percentage point excess over the growth rate of mean income is cleverly shown to equal the percentage decrease in an inequality index—one of these is new, being "similar to the Gini index in logarithmic scale"; the other is an Atkinson (1970) index. The authors envisage using these excess growth rates as pro-poorness indicators (see Son and Kakwani, 2008, especially pp. 1050, 1058).

definitionally be no pro-poorness, which is not so in our simulations: the density of scatterpoints on our vertical axes indicates the possibilities for conventionally defined pro-poor and pro-rich growth patterns to have zero net inequality effects.

6. Concluding Remarks

A significant finding from our simulations has perhaps been underplayed. Although the PPIE sectors in all scenarios are almost empty, *they are not completely empty*. The basic intuition we spoke of at the outset, that pro-poor growth, being focused more toward the poor than inequality-neutral growth, should be inequality-reducing, though essentially confirmed by our study, is however slightly imperfect. Pro-poorness does not sufficiently constrain growth patterns as to rule out small inequality increases for each of the distributions considered.

This raises an apparent conundrum. If PRIR is so frequently observed, surely PPIE should be as often observed, as a result of converse moves from final distributions back to the initial one?[12] Thus, how can the PRIR sectors in our scatters be so thickly populated, whilst the PPIE sectors are almost empty? The answer points to an important issue for pro-poorness measurement. In moving from base to final distribution, the poverty line is 50 percent of the base median. For converse moves, although aggregate income returns back to the base value and inequality increases back to the base value, *in every case we start from a different poverty line.*[13] The pro-poorness relation is not necessarily transitive if the poverty line is varied. That is, a transition from regime A to regime B may be pro-poor, and also a transition from B to C, but if the poverty line is changed at B, then the transition from A to C cannot be vouched to be pro-poor. This issue was first pointed out by Duclos (2009).

Our approach is driven by the use of parametric distributions that fit the data well, but it is worth pointing to a quite distinct, non-parametric approach that has recently been articulated by Anderson (2012), in which the implications of stochastic theories for the evolution of income distribution are explored. In particular, if different stochastic processes are at work in economically different groups in society, then the poor may be identified “by the extent to which their income processes are noticeably different from the income processes of other groups in society rather than because their income is less than some pre-specified boundary” (Anderson, 2012, p. 16). This interesting idea would evidently lead to an entirely different perspective on the growth, inequality, and pro-poorness nexus.

Throughout the developing world, poverty reduction has been below what distributionally neutral growth would have achieved: growth has oftentimes failed to be inclusive. In respect of the “distressingly little evidence of inclusiveness in India’s consumption growth experience,” which Jayaraj and Subramanian (2012)

[12]This question was posed to us by Florent Bresson, and we thank him for it.

[13]As an example from our simulations, we took a point in PRIR representing a transition in which the mean fell by 5 percent and pro-poorness for the Watts index was –1.721. For the converse transition, the mean and Gini rose back to their original (base) values, but the poverty line now becomes half of the *final* median, a reduction of 4.6 percent on the starting value. Only final incomes up to that lower value count as poor in the return to the base distribution. Pro-poorness becomes –0.575, i.e. the converse transition is still pro-rich, but much less so.

uncovered, these authors go so far as to suggest that "the facts and values that seem to inform the State's policy imperatives (as distinct from its rhetoric) in the matter of 'inclusive growth' constitute a serious affront to both political morality and enlightened self interest" (pp. i, 31). Be that as it may, the impact of growth on poverty as well as on inequality is clearly a concern for policymakers in all countries. We hope to have shed light on the possibilities by means of this simulation-based investigation of the pro-poorness, growth, and inequality nexus.

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