Robust "pro-poorest" poverty reduction with counting measures: the non-anonymous case

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Contents

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- Examples: Kacem (2013) uses a non-monetary index of wellbeing of poverty as the initial condition, and the checks whether income growth is pro-poor.
- Examples: Boccanfuso et al. (2009) apply the continuous-variable toolkit to deprivation scores of a non-monetary poverty index based on MCA.

This paper's question

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- What are the conditions under which a poverty reduction experience is *robustly* more "pro-poorest" than another one, in the context of counting measures of multidimensional poverty?
- Under which conditions does poverty reduction not only reduce the average poverty score further but also decrease deprivation inequality among the poor, in a robust manner?

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- When our conditions are met, one can state that poverty reduction is more egalitarian in one experience (vis-a-vis another one) for a broad family of poverty indices which are sensitive to deprivation inequality among the poor, and from an *ex-ante* conception of inequality of opportunity.

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- When our conditions are met, one can state that poverty reduction is more egalitarian in one experience (vis-a-vis another one) for a broad family of poverty indices which are sensitive to deprivation inequality among the poor, and from an *ex-ante* conception of inequality of opportunity.
- We derive three necessary and sufficient conditions, plus two sufficient conditions, which all involve comparing the distributions of conditional expected deprivation scores induced by mobility matrices. The different conditions relate to different ways in which we can construct the distributions of expected scores.

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2. The transition 2008-2010 dominates all the others when the distribution of expected scores is weighted by the initial relative frequencies of conditioning scores.
3. The transitions 2002-2004 and 2008-2010 dominate all the other when the distribution of expected scores is weighted by the ergodic distribution of scores.

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Social poverty functions:

$$P = \frac{1}{N} \sum_{n=1}^{N} p_n \quad (2)$$

Preliminaries: Axioms

FOC

P should not be affected by changes in the deprivation score of a non-poor person as long as for this person it is always the case that: $c_n < k$.

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PROG

A rank-preserving transfer of a deprivation from a poorer individual to a less poor individual, such that both are deemed poor, should decrease P.

Preliminaries: Social poverty indices

$$P = \frac{1}{N} \sum_{n=1}^{N} \mathbb{I}(c_n \geq k) g(c_n), \tag{3}$$

where:

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where:

- $\mathbb{I}(c_n \geq k)$ is the Alkire-Foster poverty identification function securing fulfillment of FOC;
- $g : c_n \rightarrow [0, 1]$, such that: $g(0) = 0$, $g(1) = 1$, $g' > 0$ and $g'' > 0$. g captures the intensity of poverty, which is understood as number of deprivations in the counting approach. Several examples of g have been proposed by Chakravarty and D'Ambrosio (2006).

Possible values of the score

- Vector of possible values of c_n given z and W:
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- Note: $v_1 = 0$, $v_I = 1$, $\max I = \sum_{i=0}^{D} \binom{D}{i}$, $I = D + 1$ if $w_d = \frac{1}{D}\ \forall d$.
- Hence distribution of c_n is *discrete*.

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- Finally, we can provide social evaluations of the distributions of conditional expected scores. For instance, we may want these evaluations to satisfy MON and PROG.
- Thus we rank transition matrices in terms of their capacity to reduce poverty, prioritizing reductions in the expected deprivation score of those who start the poorest.
- If applied to generations or long time periods, it also provides an assessment of ex-ante inequality of opportunity.

Some more required notation

Transition probability: $m_{i|j} = \Pr[c_n^t = i | c_n^{t-1} = j]$; from transition matrix M.

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$$E[c_n^t | v_j] = 0 \times m_{0|v_j} + v_2 \times m_{v_2|v_j} + v_3 \times m_{v_3|v_j} + ... + 1 \times m_{1|v_j}, \quad (4)$$

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Distribution of actual scores in period $t-1$:
$\Pi := [\pi(0), \pi(v_2), ...\pi(1)]$.

One important assumption

Assumption 1

$$E[c_n^t|1] \geq E[c_n^t|v_{l-1}] \geq ... \geq E[c_n^t|v_2] \geq E[c_n^t|0].$$

A reversed generalized Lorenz (RGL) curve of expected deprivation scores

$$L(s) = \frac{1}{I} \sum_{j=1}^{s} E[c_n^t | v_{I-j+1}] \quad s = 1, 2, ..., I. \tag{5}$$

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$\frac{1}{I}\sum_{j=1}^{I} g(E^A[c_n^t|v_j]) < \frac{1}{I}\sum_{j=1}^{I} g(E^B[c_n^t|v_j])$ for all convex, strictly increasing, continuous functions g, if and only if $L^A(s) \leq L^B(s) \;\; \forall s \in [1, 2, ..., I] \;\; \wedge \exists s | L^A(s) < L^B(s)$.

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When theorem 1 holds, M^A induces a stronger reduction in poverty than M^B, in terms of prioritizing the expected deprivation scores of those who start with higher scores in $t-1$ (under assumption 1).

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The theorems can also be adjusted to more stringent poverty identification approaches.

The case with equal initial distributions of deprivation scores

Theorem 2

$\frac{1}{l}\sum_{j=1}^{l}\pi(v_j)g(E^A[c_n^t|v_j]) < \frac{1}{l}\sum_{j=1}^{l}\pi(v_j)g(E^B[c_n^t|v_j])$ for all convex, strictly increasing, continuous functions g, and for every possible Π, if and only if $E^A[c_n^t|v_j] < E^B[c_n^t|v_j] \;\; \forall j \in [1, 2, ..., l]$.

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Note the importance of vector dominance in this situation.

The case with different initial distributions of deprivation scores

We use a slightly different RGL curve:

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Theorem 3

$\sum_{j=1}^{l} \pi^A(v_j) g(E^A[c_n^t | v_j]) < \sum_{j=1}^{l} \pi^B(v_j) g(E^B[c_n^t | v_j])$ for all convex, strictly increasing, continuous functions g, if and only if $L^A(s) \leq L^B(s) \ \ \forall s \in [1, 2, ..., l] \ \ \wedge \exists s | L^A(s) < L^B(s)$.

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Proposition 1

If $(E^A[c_n^t|v_{I-j+1}] - E^A[c_n^t|v_{I-j}]) \leq (E^B[c_n^t|v_{I-j+1}] - E^B[c_n^t|v_{I-j}]) \forall j \in [1, 2, ..., I-1] \ \wedge E^A[c_n^t|v_1] \leq E^B[c_n^t|v_1]$ (with at least one of the former inequalities being strict), *and* $H^A(v_i) \leq H^B(v_i) \ \forall i \in [1, 2, ..., I] \ \wedge \exists i | H^A(v_i) < H^B(v_i)$, then: $L^A(s) \leq L^B(s) \quad \forall s \in [1, 2, ..., I] \ \wedge \exists s | L^A(s) < L^B(s)$.

The case with different ergodic distributions of deprivation scores

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But there is an interesting sufficient condition:

Proposition 2

$\sum_{j=1}^{l} \hat{\pi}^A(v_j) g(E^A[c_n^t|v_j]) < \sum_{j=1}^{l} \hat{\pi}^B(v_j) g(E^B[c_n^t|v_j])$ for all convex, strictly increasing, continuous functions g, if $\forall j \in [1, 2, ..., l]$: $\sum_{i=1}^{q} m^A_{v_i|v_j} \geq \sum_{i=1}^{q} m^B_{v_i|v_j}$ $\forall q \in [1, 2, ..., l]$ $\wedge \exists q | \sum_{i=1}^{q} m^A_{v_i|v_j} > \sum_{i=1}^{q} m^B_{v_i|v_j}$.

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- The financial crisis affected Peru's performance, but monetary poverty kept decreasing.
- How did the population fare in terms of non-monetary multidimensional poverty?

Data

We use the Peruvian National Household Surveys (ENAHO). Two recent household panel surveys, spanning 2002-2006 and 2007-2010, each providing 1,570 and 2,260 households, respectively.

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We focus on households and measure poverty with 4 dimensions, each weighted equally. Therefore: $V = (0, 0.25, 0.5, 0.75, 1)$.

Data: the poverty dimensions used

- **Education**. Deprived if either: (1) at least one member of school age at least delayed one year; (2) at least one adult member without complete primary; or (3) both.

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- **Service access**. Deprived if either: (1) lack of electricity; (2) lack of piped water; (3) lack of sewerage or septic tank; (4) lack of telephone landline.
- **Vulnerability to dependency burden**. Deprived if dependency ratio (people below 15 or above 65 / people between 15-65) higher than 3.

Period 2002-2004

Table : Transition matrix of deprivation scores, Peru, 2002-2004

		2002				
		0	0.25	0.5	0.75	1
	0	0.87	0.21	0.02	0.0	0.0
	0.25	0.11	0.65	0.20	0.04	0.0
2004	0.5	0.02	0.14	0.67	0.33	0.09
	0.75	0.0	0.0	0.11	0.61	0.36
	1	0.0	0.0	0.0	0.02	0.55
	π	0.18	0.28	0.36	0.17	0.01
	$E[c_n^t \mid j]$	0.039	0.235	0.467	0.653	0.864
	$\hat{\pi}$	0.47	0.27	0.20	0.06	0.00

Period 2004-2006

Table : Transition matrix of deprivation scores, Peru, 2004-2006

		2004				
		0	0.25	0.5	0.75	1
	0	0.82	0.19	0.02	0.0	0.0
	0.25	0.15	0.68	0.19	0.03	0.0
2006	0.5	0.03	0.12	0.69	0.21	0.0
	0.75	0.0	0.01	0.11	0.74	0.58
	1	0.0	0.0	0.0	0.02	0.42
	π	0.23	0.28	0.34	0.15	0.01
	$E[c_n^t \mid j]$	0.051	0.239	0.473	0.686	0.854
	$\hat{\pi}$	0.35	0.31	0.23	0.11	0.00

Period 2007-2008

Table : Transition matrix of deprivation scores, Peru, 2007-2008

		2007				
		0	0.25	0.5	0.75	1
	0	0.88	0.14	0.01	0.0	0.0
	0.25	0.10	0.71	0.15	0.01	0.0
2008	0.5	0.02	0.14	0.74	0.24	0.0
	0.75	0.0	0.0	0.10	0.74	0.40
	1	0.0	0.0	0.01	0.01	0.60
	π	0.27	0.27	0.29	0.15	0.01
	$E[c_n^t \mid j]$	0.034	0.251	0.489	0.686	0.900
	$\hat{\pi}$	0.33	0.26	0.28	0.12	0.01

Period 2008-2010

Table : Transition matrix of deprivation scores, Peru, 2008-2010

		2008				
		0	0.25	0.5	0.75	1
	0	0.86	0.17	0.03	0.0	0.0
	0.25	0.13	0.68	0.24	0.05	0.0
2010	0.5	0.01	0.14	0.64	0.26	0.05
	0.75	0.0	0.01	0.10	0.67	0.25
	1	0.0	0.0	0.0	0.02	0.70
	π	0.283	0.267	0.293	0.148	0.01
	$E[c_n^t \mid j]$	0.039	0.250	0.451	0.666	0.913
	$\hat{\pi}$	0.43	0.32	0.18	0.06	0.00

Theorem 1

Table : RGL curves of expected deprivation scores (as defined in 5). Vertical coordinates.

	1	2	3	4	5
2004|2002	0.836	1.516	1.983	2.218	2.257
2006|2004	0.854	1.540	2.013	2.252	2.304
2008|2007	0.900	1.586	2.074	2.325	2.359
2010|2008	0.913	1.578	2.029	2.279	2.318

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2004|2002	0.836	1.516	1.983	2.218	2.257
2006|2004	0.854	1.540	2.013	2.252	2.304
2008|2007	0.900	1.586	2.074	2.325	2.359
2010|2008	0.913	1.578	2.029	2.279	2.318

M^{2002-4} dominates all the others. M^{2004-6} dominates the other two. M^{2007-8} and $M^{2008-10}$ cannot be ordered between themselves.

Theorem 2

Table : Conditional expected deprivation scores

Transition c_n^{t-1}	0	0.25	0.5	0.75	1
2004|2002	0.039	0.235	0.467	0.652	0.864
2006|2004	0.051	0.239	0.473	0.686	0.854
2008|2007	0.034	0.251	0.489	0.686	0.900
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No ordering is robust.

Theorem 3 with initial distributions

Table : RGL curves of expected deprivation scores (as defined in 6, using initial distributions). Vertical coordinates.

	1	2	3	4	5
2004|2002	0.006	0.120	0.287	0.351	0.358
2006|2004	0.007	0.109	0.270	0.336	0.348
2008|2007	0.008	0.114	0.255	0.324	0.333
2010|2008	0.008	0.107	0.239	0.306	0.317

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$M^{2008-10}$ dominates all the others. M^{2002-4} is dominated by all the others. M^{2004-6} and M^{2007-8} cannot be ordered between themselves.

Theorem 3 with ergodic distributions

Table : RGL curves of expected deprivation scores (as defined in 5, using ergodic distributions). Vertical coordinates.

	1	2	3	4	5
2004|2002	0.002	0.041	0.136	0.199	0.217
2006|2004	0.000	0.074	0.182	0.256	0.274
2008|2007	0.008	0.092	0.228	0.294	0.305
2010|2008	0.000	0.043	0.125	0.206	0.223

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$M^{2008-10}$ and M^{2002-4} dominate the others, but cannot be ordered between them. M^{2004-6} dominates M^{2007-8}.

Concluding remarks

- All proposed non-anonymous assessment methods check for second-order dominance among expected deprivation scores. When it happens, it means that one distribution of expected deprivation scores is preferrable in the sense, not only of yielding lower average expected scores, but also that expected scores that are more "pro-poorest", i.e. prioritize the reduction of the highest expected scores.

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- However there are alternative ways of defining the distributions of expected scores. We proposed four ways: (1) just the scores, (2) equal initial distributions, (3) actual initial distributions, (4) ergodic distributions.

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- Results were sensitive to these choices: (1) favoured 2002-2004 (best expected scores); (3) favoured 2008-2010 (best initial distribution); (4) favoured 2002-2004 and 2008-2010 ("intermediate result"?); (2) could not yield even one pairwise order.

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- To do: Proper inference, revise choice of indicators? Suggestions?