

HOW MUCH DOES REDUCING INEQUALITY MATTER FOR GLOBAL POVERTY?

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Motivation

- From 1990 to 2015, the global poverty rate decreased from 35.6% to 10.0%.
- Goals of ending extreme poverty by 2030 have been expressed as:
 - SDGs: “eradicate extreme poverty for all people everywhere”
 - World Bank (2013): reduce to 3% by 2030
- With growth at current/historical levels, this goal will not be achieved.
- This paper seeks to quantify the importance of reducing inequality in getting closer to these goals.

Contribution

A number of papers on this topic:

Birdsall et al., 2014; Chandy et al., 2013; Edward and Sumner, 2014; Karver et al., 2012; Hellebrandt and Mauro, 2015; Hillebrand, 2008; Higgins and Williamson, 2002; Hoy and Samman, 2015; Ravallion, 2013; Yoshida et al., 2014.

We offer four contributions to the literature:

1. We have an unprecedented data coverage
2. We model distributional changes using the Gini index
3. We use growth incidence curves to capture distributional changes
4. We use a novel machine-learning algorithm to model how growth in GDP/capita is passed through to growth in welfare

Data Coverage

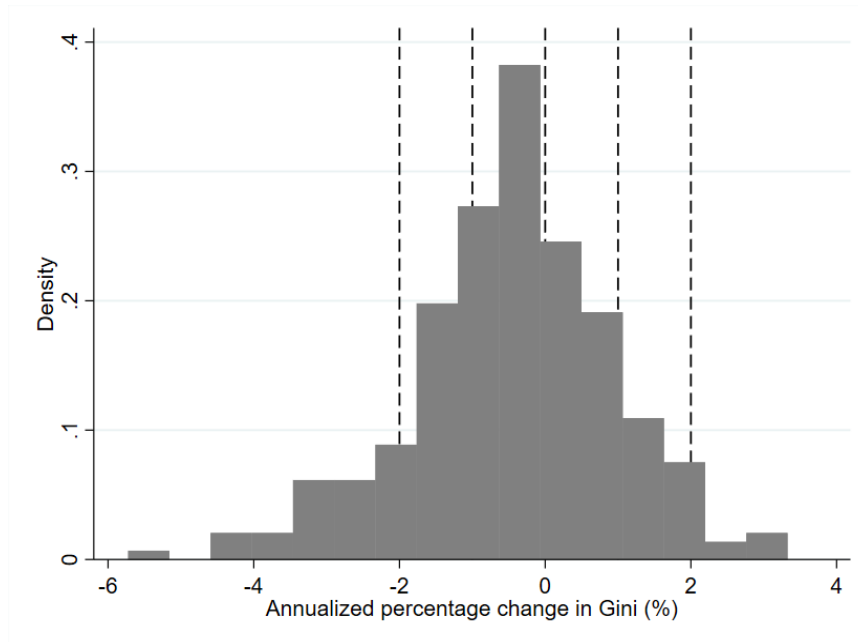
Poverty data

- Use data from PovcalNet:
<http://iresearch.worldbank.org/PovcalNet/>
 - Microdata for 120 countries ~64% of the world's population
 - Binned data (400 bins) for 35 countries ~14% of the world's population
 - Grouped data (5/10 groups) for 9 countries ~20% of the world's population
- In total, 164 countries covering ~97% of the world's population

Inequality Scenarios

Inequality Scenarios

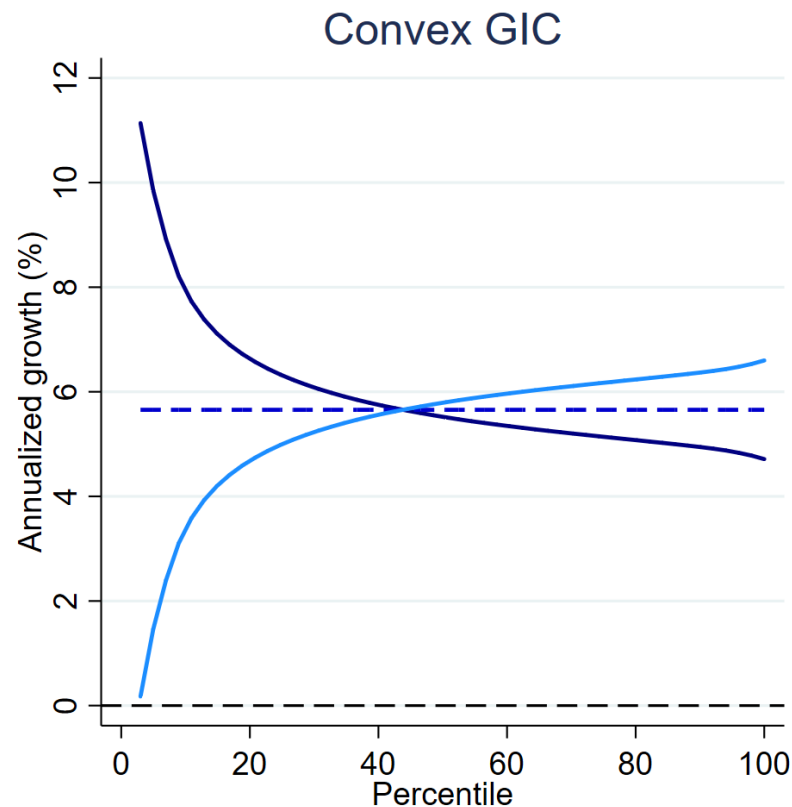
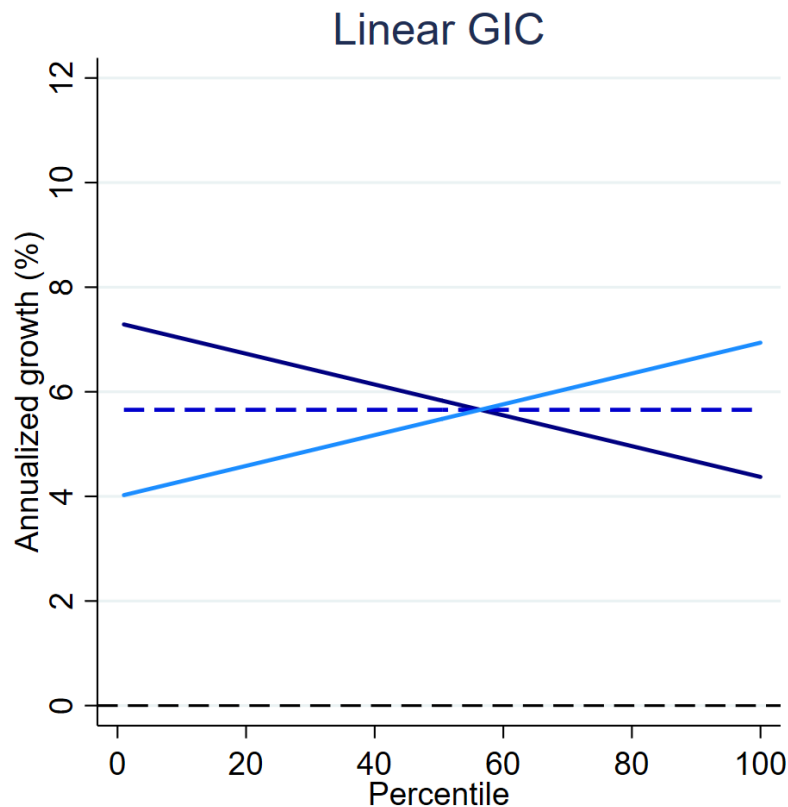
- Assume the Gini changes by -2, -1, 0, 1 or 2% per year
- Such changes are all historically plausible



Growth Incidence Curves

- There are infinitely many ways a change in the Gini can come about
- We use growth incidence curves (GICs) to implement changes in the Gini in a plausible manner
- $y_{p,t+1} = y_{p,t}(1 + g_p)$, $p = \text{percentile group}$
- We will work with two different growth incidence curves:
 1. Linear GIC: $g_p = \delta - \theta p$
 2. Convex GIC: $g_p = (1 - \tau)(1 + \gamma) - 1 + [\tau(1 + \gamma)\mu_t] \frac{1}{y_{p,t}}$,
 $\tau = \text{flat tax rate}, \gamma = \text{mean growth}, \mu = \text{mean}$

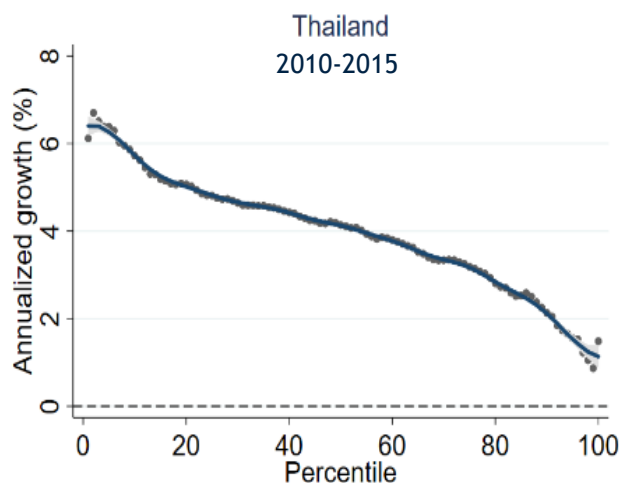
Different GICs with same change in Gini



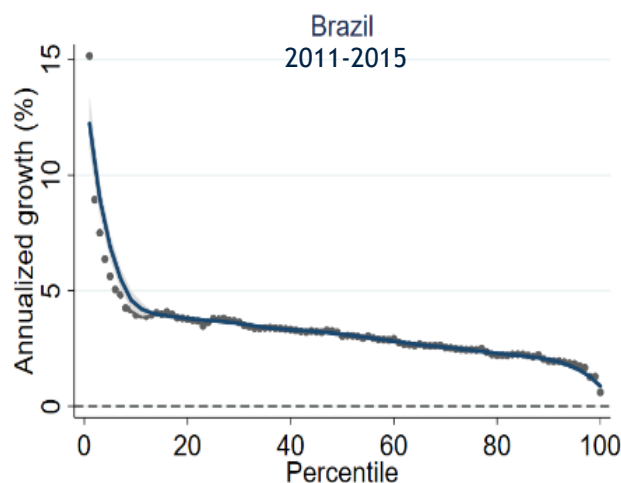
— Gini drops by 1% - - - No change in Gini — Gini increases by 1%

Empirically observed GIC's

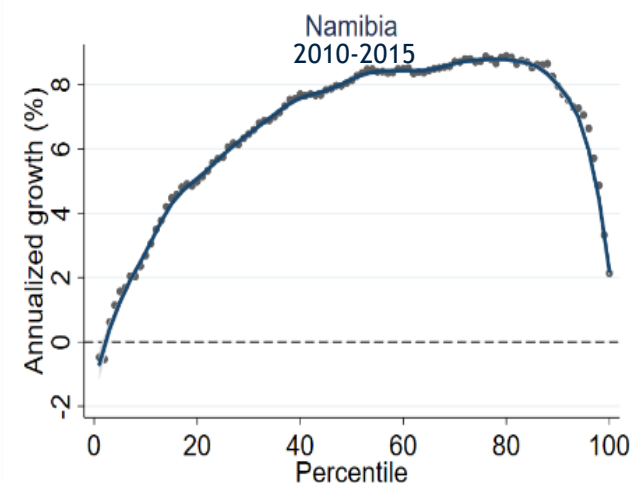
Approximately linear



Approximately convex



Other shape



Growth Scenarios

Growth scenarios

- To project poverty forward we need to make assumptions about growth rates
- We look at three different growth scenarios
 1. Each country grows according to its growth rate in GDP/capita from 1997-2017
 2. Each country grows according to its growth rate in GDP/capita from 2007-2017
 3. Each country grows according to its growth forecast in GDP/capita from 2018-2013
- Historically, only a fraction of growth in GDP/capita is passed through to growth observed in surveys
$$g_{survey} = \beta * g_{GDP/capita} + \varepsilon, \quad \beta = \text{passthrough rate} < 1$$

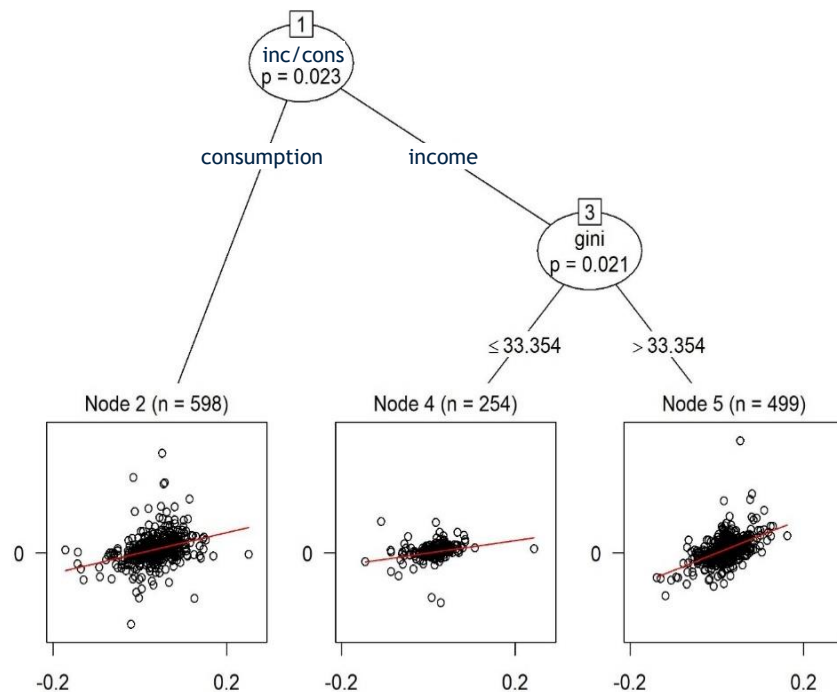
Estimating passthrough rates

Estimate β through Model-Based Recursive Partitioning:

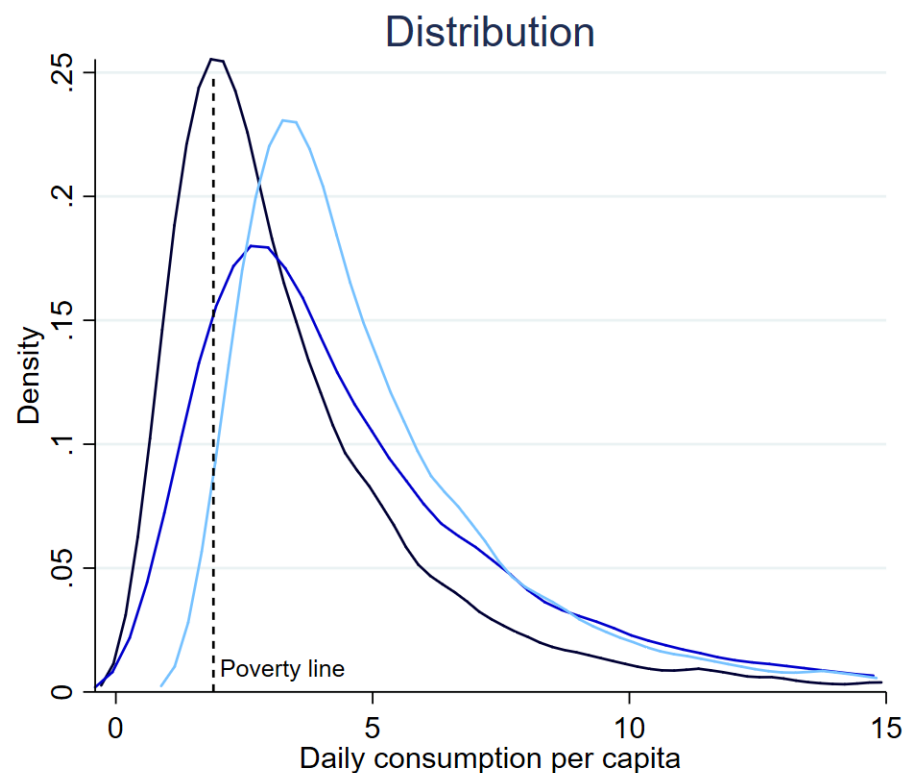
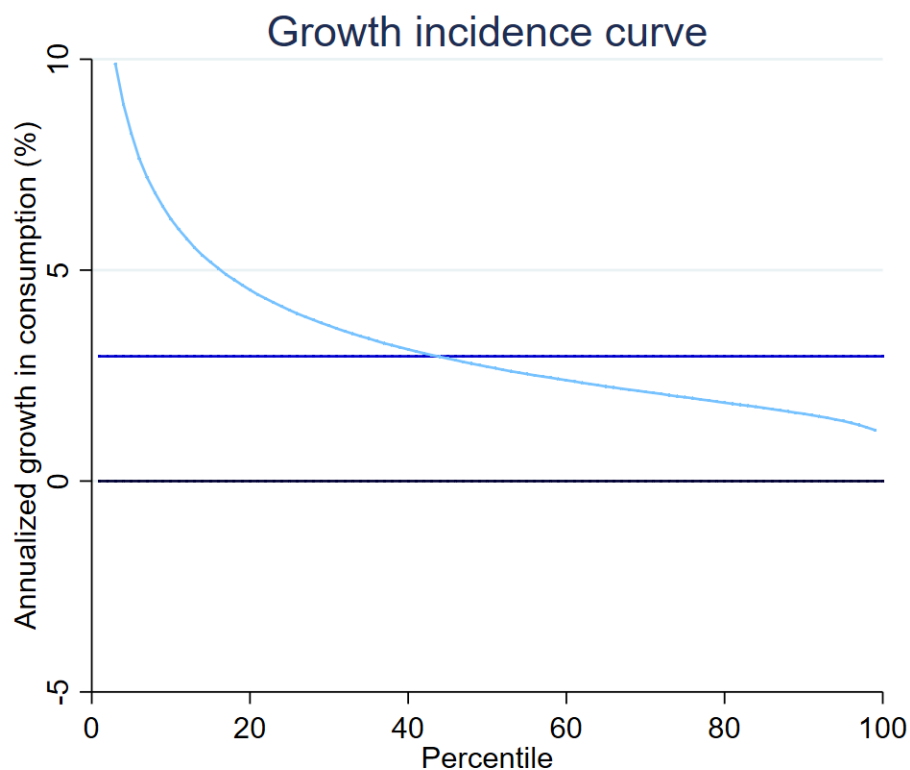
1. Run the regression $g_{survey} = \beta * g_{GDP/capita} + \varepsilon$ on all relevant data.
2. Add interactions between $g_{GDP/capita}$ and relevant variables separately, and conduct Wald tests indicating whether the interaction coefficient(s) are statistically significant.
3. If the lowest p-value of these tests is greater than 0.05, nothing is done, and the algorithm stops. If the lowest p-value is less than 0.05, then the variable with the lowest p-value is chosen as a splitting variable.
4. The sample is split into two using the splitting variable.
5. The algorithm is repeated from the beginning by applying it to observations in each of the two subsamples separately.

Model-Based Recursive Partitioning

Node	Obs.	β	P-values from Wald tests									
			Inc/con s	Gini	Media n	Mean	GDP	World Bank region	Povcal Net region	Year	Popula tion	Headc ount
1	1351	0.83	0.023	0.22	0.90	0.16	0.11	0.99	0.99	0.99	1.00	1.00
2	598	0.71	-----	1.00	0.17	0.15	0.19	1.00	1.00	0.70	1.00	0.74
3	753	0.99	-----	0.021	0.64	0.95	0.94	1.00	0.91	0.15	0.93	0.40
4	254	0.44	-----	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.99	1.00
5	499	1.22	-----	0.98	0.99	1.00	1.00	1.00	0.75	0.46	0.86	0.93



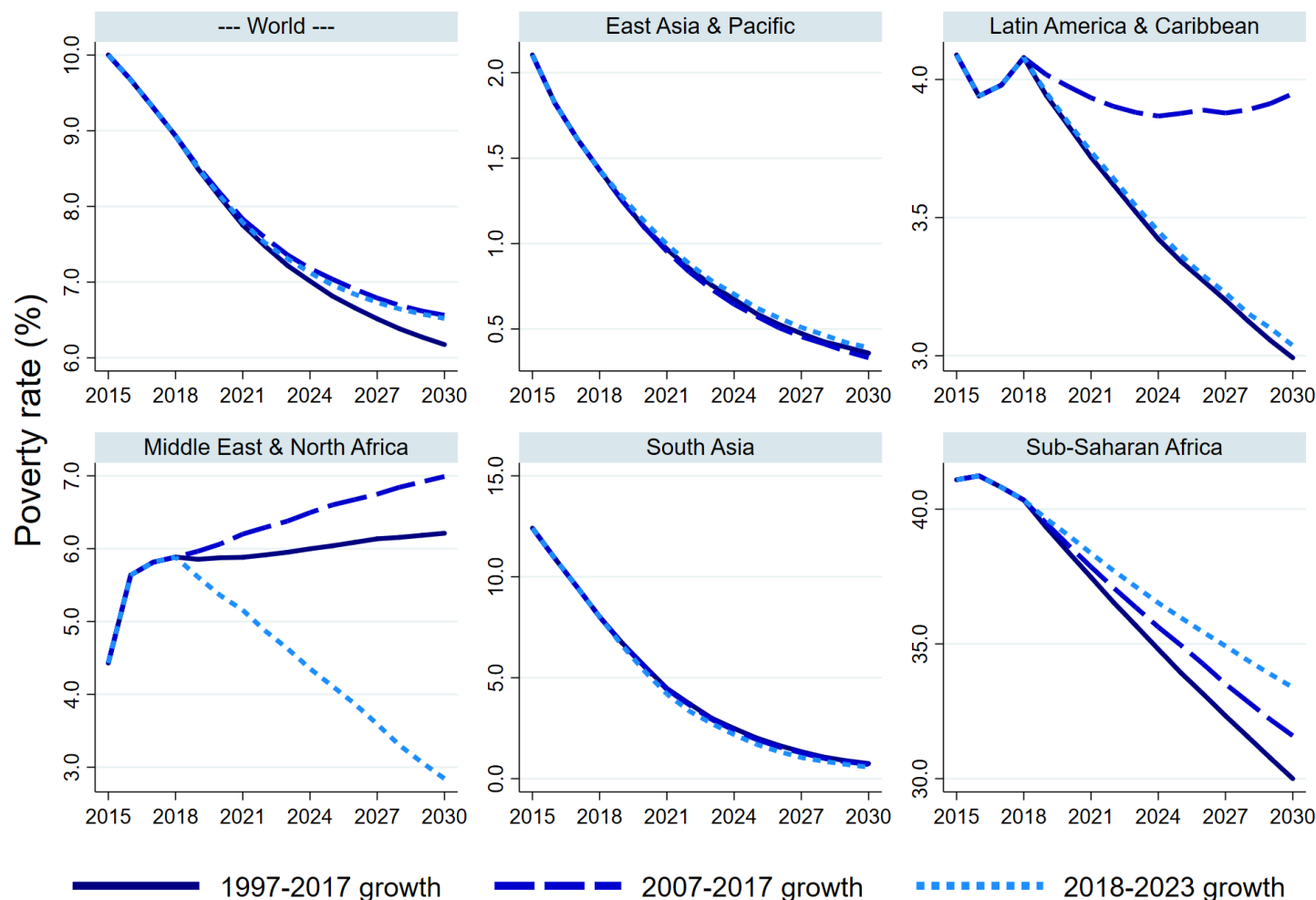
Visualization of methods



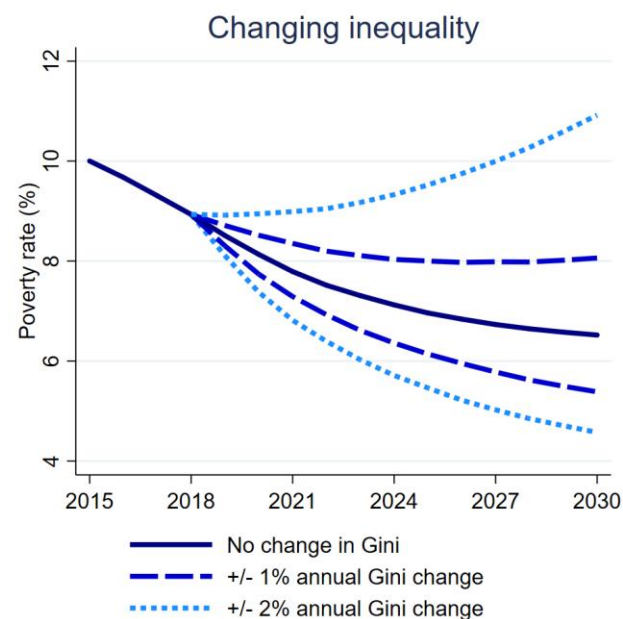
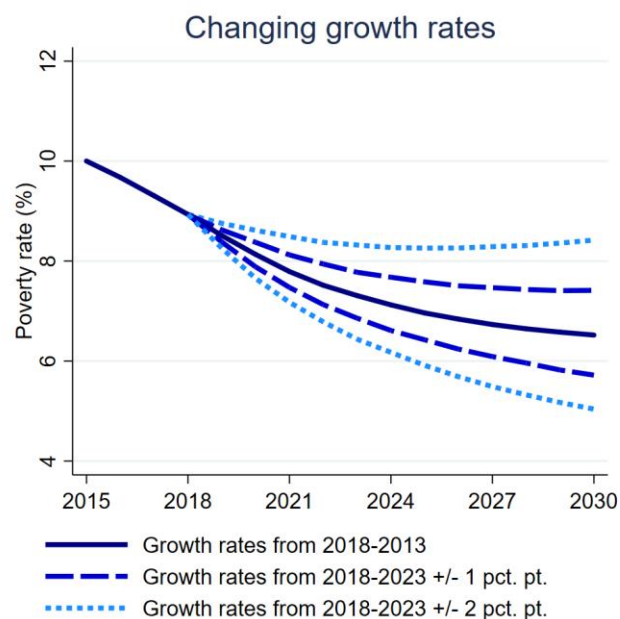
— 2018 distribution — Distribution-neutral growth — Growth w. 2% annual reduction in Gini

Results

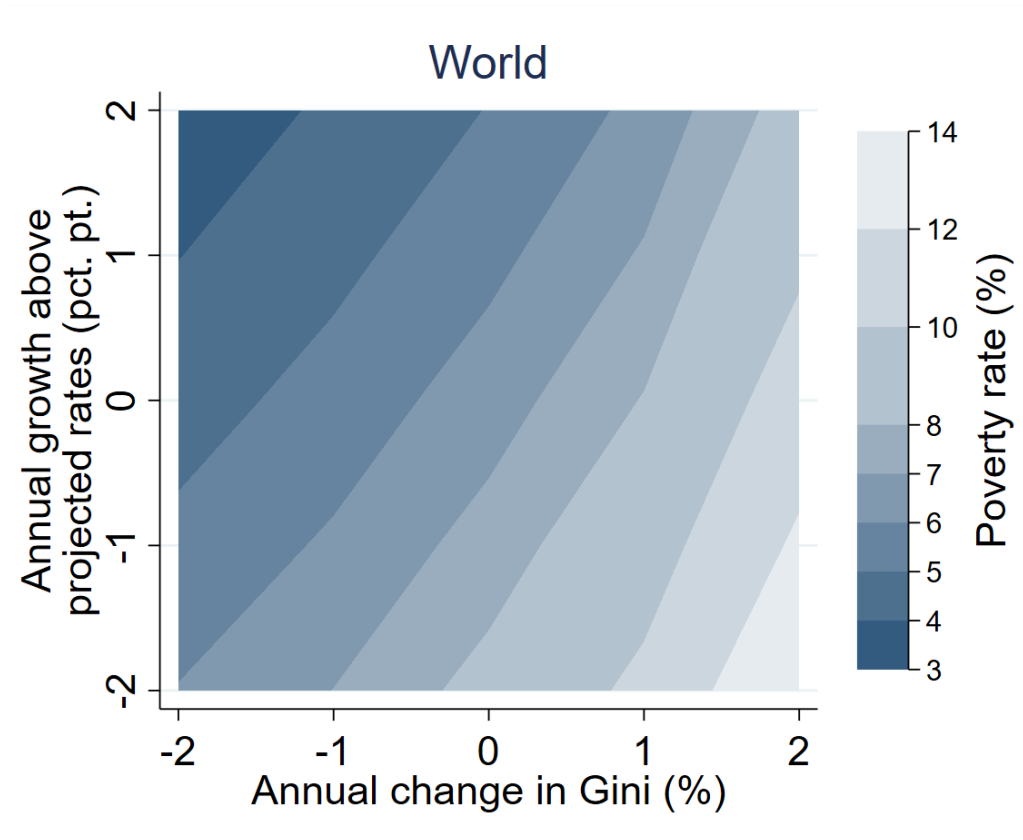
Distribution-neutral poverty projections



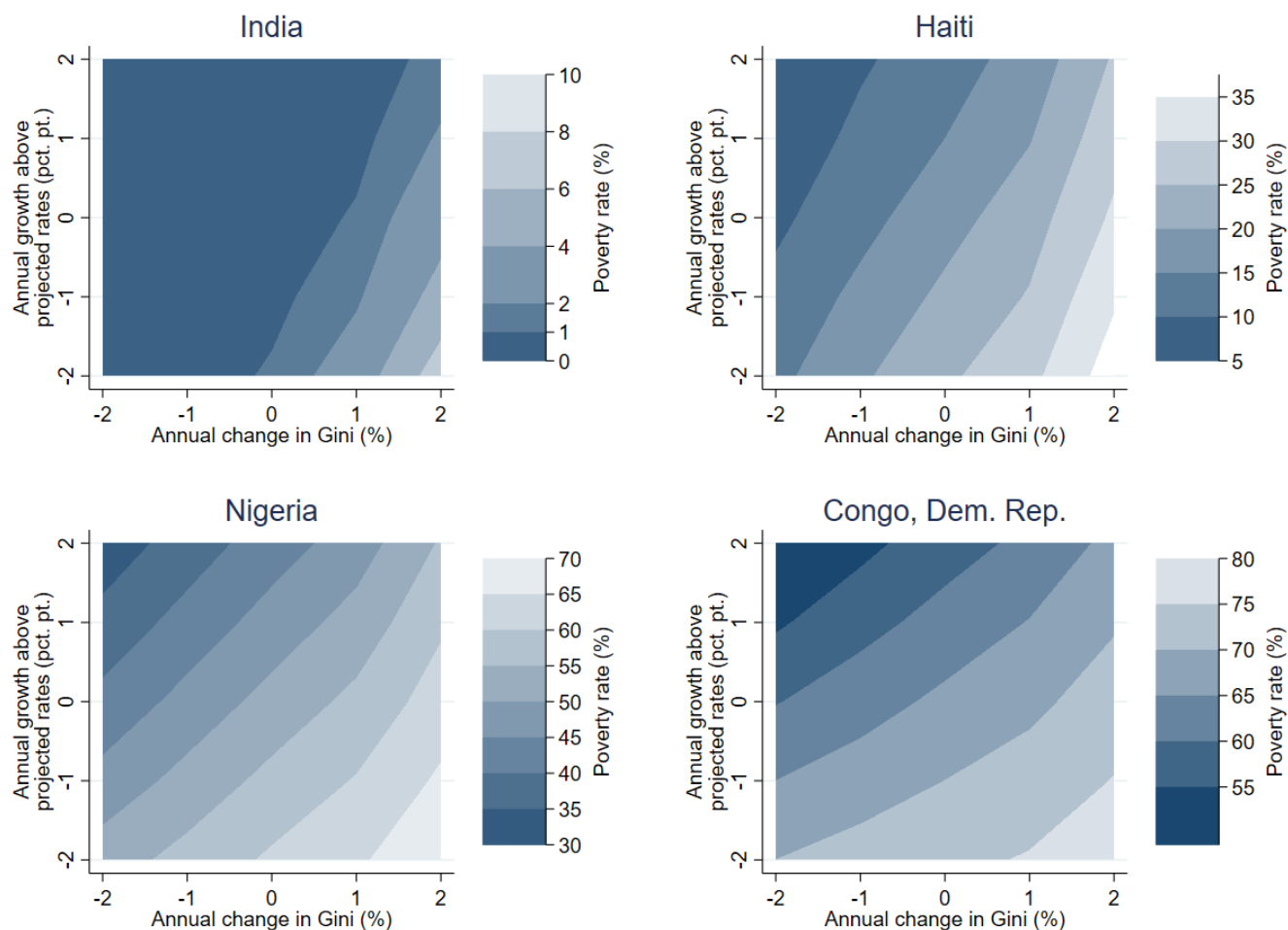
Changing growth and inequality



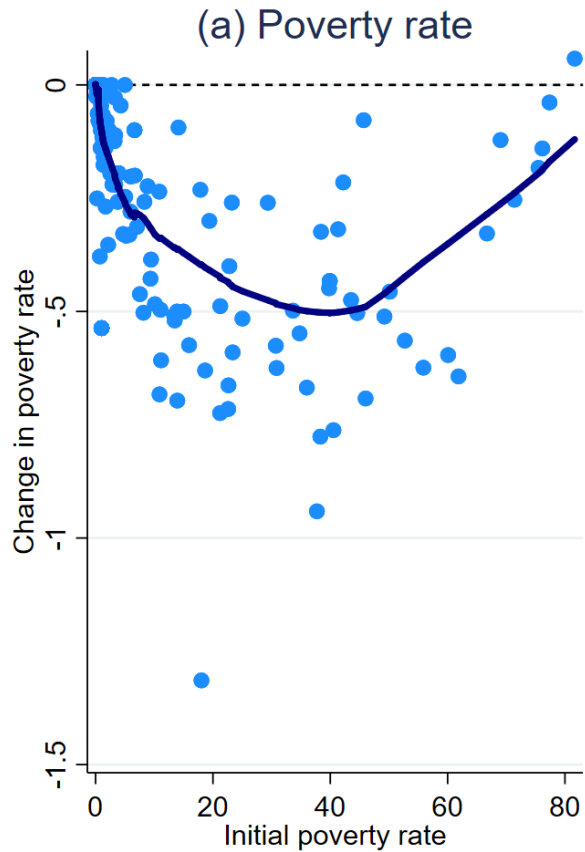
Global Iso-Poverty Curve, 2030



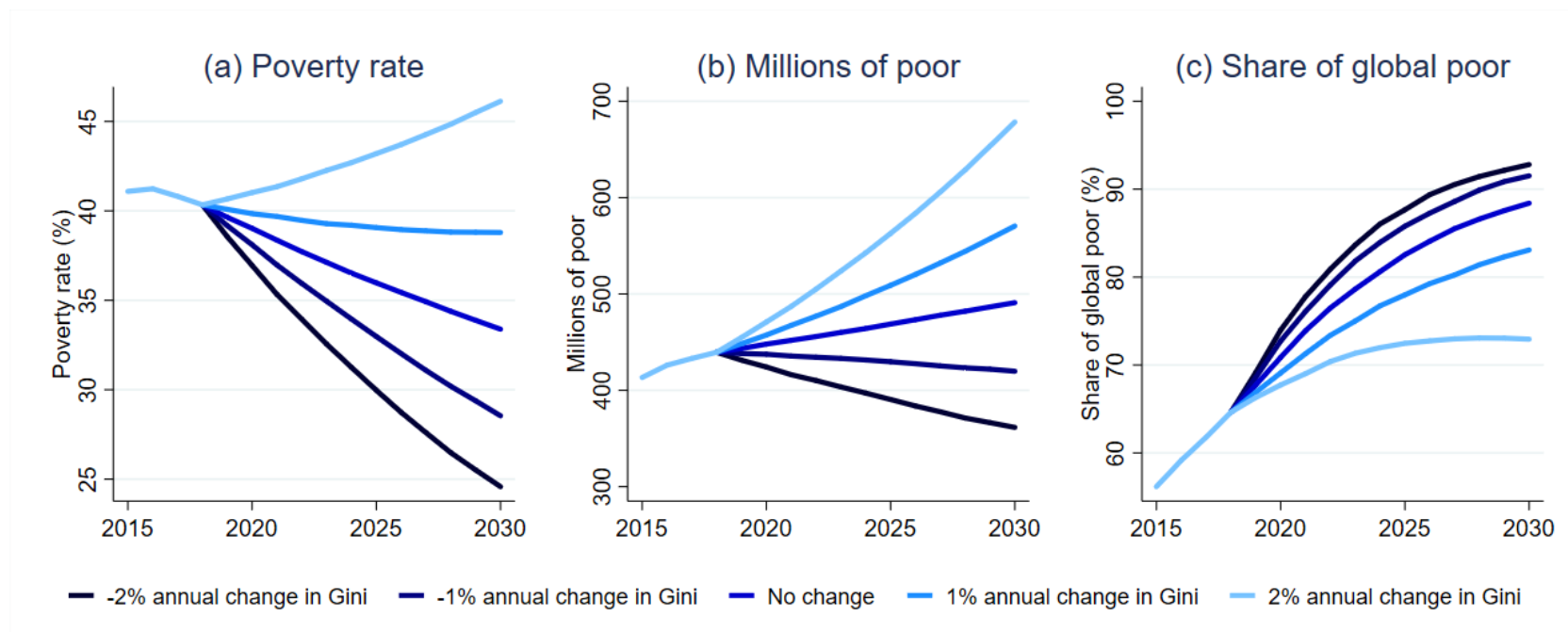
Country Iso-Poverty Curves, 2030



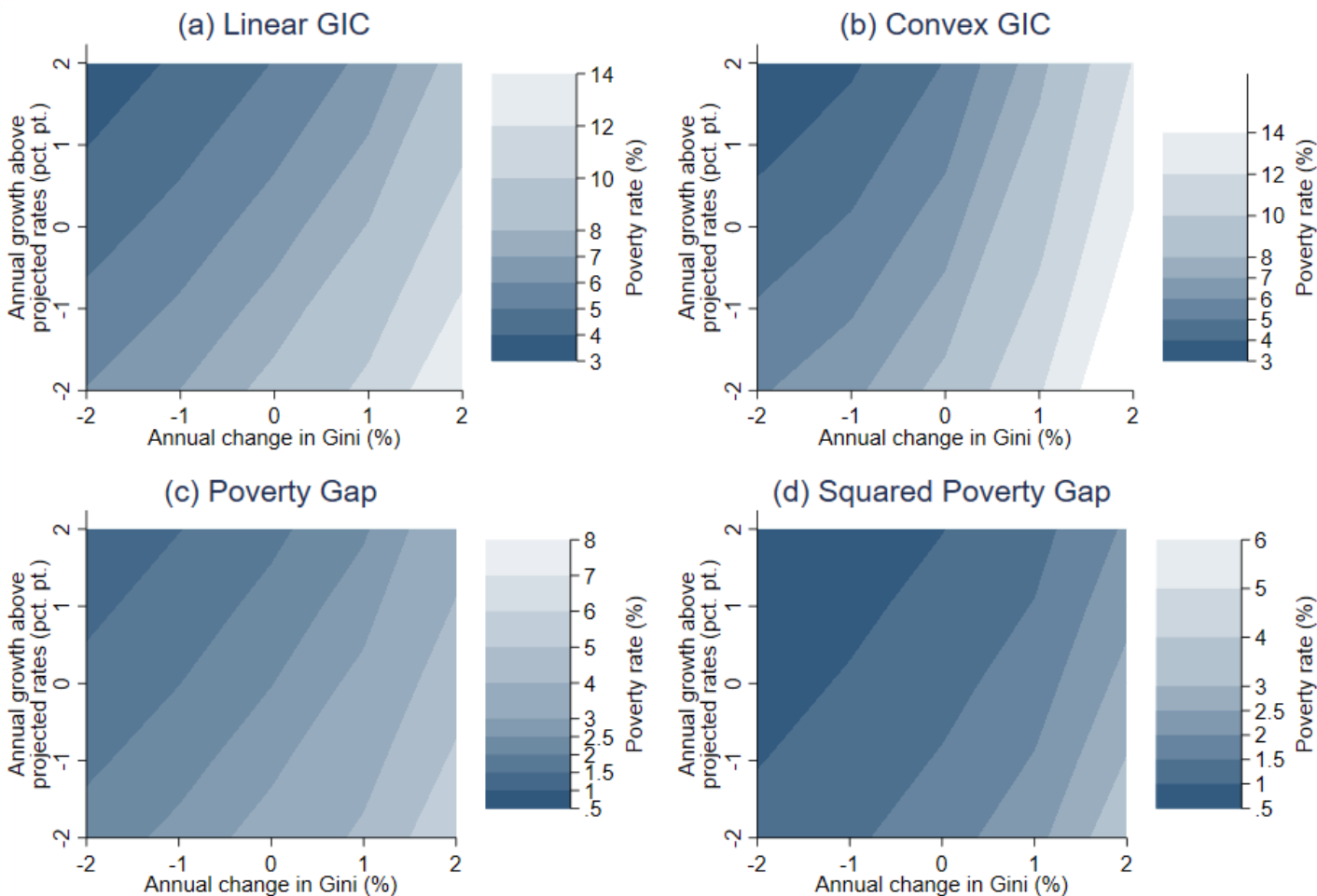
Impact of reducing Gini by 1%



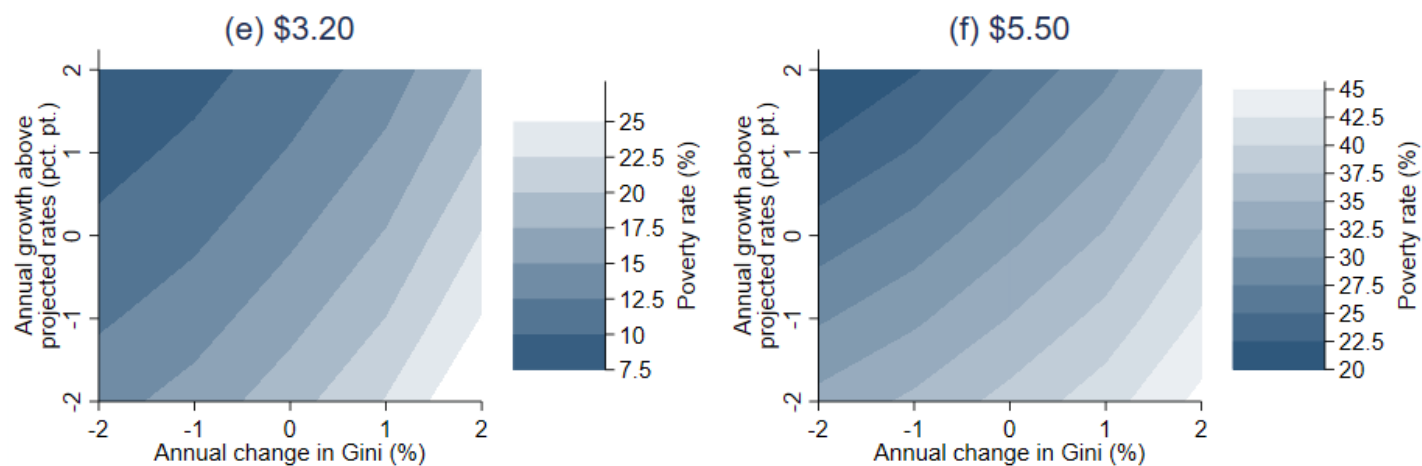
Poverty Projections in Sub-Saharan Africa



Using other poverty measures



Using higher poverty lines



Conclusion

- Under a status-quo scenario, global poverty will not reach the SDG targets by 2030
- Reducing each country's Gini index by 1% per year has a larger impact on global poverty than increasing each country's annual growth 1 percentage point above forecasts
- This may be the most viable path to get closer to the 2030 targets
- Yet for the very poorest countries, growth is more impactful than reducing inequality