Extreme incomes and the estimation of poverty and inequality indicators from EU-SILC

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Comparative EU Statistics on Income and Living Conditions: Issues and Challenges

Helsinki, 6-7 November 2006

Focus

EU-SILC is to become the reference EU data source for estimation of welfare indicators (poverty, inequality)

$\Longrightarrow$ crucial to make accurate inference!

- accurate inference involves many issues, e.g.
  - underlying concept of well-being, definition of household income, equivalence scale assumptions, quality of income measurement, choice of indicators, sampling variability, ...
- focus here on **treatment of extreme incomes**

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Extreme incomes have potentially large influence on social indicators

$\Longrightarrow$ "robustness" properties of indicators

- many common indicators are non-robust statistics
  - **Inequality indices**: e.g. Gini, GE, Atkinson, income share ratio (percentile ratio OK)
  - **Poverty indices**: e.g. average poverty gap ratio (and any FGT($\alpha > 0$)), Watts (headcount OK IF poverty line is exogenous or itself robust)
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Extreme incomes?

Identifying and qualifying extreme incomes is difficult

- Plain errors? (Data contamination)
- Accurate incomes... but inaccurate measures of underlying economic well-being? (e.g. extreme small (negative) values)
- Valid measures? (e.g. extreme rich – high-leverage points)

$\Longrightarrow$ No general strategy can be entirely satisfactory

$\Longrightarrow$ Standard response: make data adjustments before estimating social indicators to ensure extreme data effect remains "under control"

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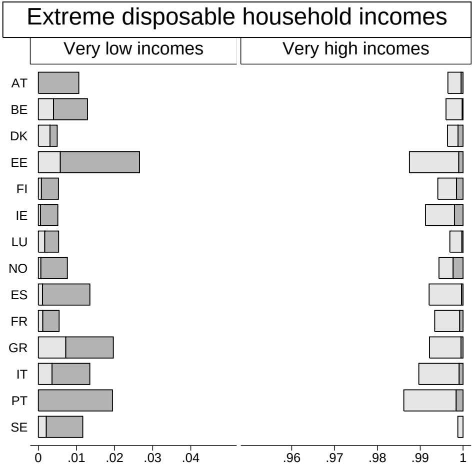
Data inspection: Components

NO as an illustrative example

Data inspection: Extreme incomes



Data adjustment procedures

A) Trimming
- extreme data contain no information
- extreme data deleted

B) Winsorizing
- extreme data contain some relevant information
- extreme data recoded to pre-defined upper/lower limits

C) Parametric tail modeling
- extreme data contain relevant information but with “noise”
- estimate underlying parametric distribution with “robust” methods and impute extreme data from the estimated distribution

D) (Removing sub-groups)
- income components measured unreliably are source of extreme data
- remove households relying largely on such sources

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Social indicators considered

Central tendency mean and median equivalent income

Inequality percentile ratios (P80/P20 and P90/P10); income share ratios (S80/S20 and S90/S10); Gini coefficient; Generalized Entropy measures (GE(0), GE(1), GE(2)); Atkinson inequality measures (A(0.5), A(1), A(2))

Poverty Foster-Greer-Thorbecke indices (FGT(0), FGT(1), FGT(2)); median poverty gap ratio among the poor (with poverty line set at 60% and 50% of the median equivalent income)

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Ordinality in cross-country comparisons is generally preserved, irrespectively of the data adjustment procedure applied.

Lesson 2

Cardinal comparisons of countries are sensitive to data adjustments made to control for extreme income data.

- e.g. ineq/poverty reductions of 10%-20% by adjusting less than 1% of data is common (sometimes much more extreme impact)
- cross-country variations in the impact of adjustments
- (most pov/ineq measures can be affected, even percentile-based indicators)

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Poverty measures are not notably less sensitive to the treatment of extreme incomes than inequality measures.

Poverty sensitive to extreme low incomes and inequality mostly sensitive to extreme high incomes.

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Generalized Entropy measures and Atkinson inequality measures suffer from either estimation impossibility with non-positive values or from higher sensitivity to extreme incomes. FGT(1+) indices also very sensitive. Data adjustement make a big difference here.

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Adjustments that modify/impute extreme data lead to results that are markedly more stable than trimming procedures. (Quantile-based indices are unaffected.)

Lesson 6

Data adjustment based on parametric-tail imputation seem to perform well... and may be judged preferable to trimming (given "cleanliness" of data)??

- 'self-adjusting' to the amount of extreme values
- optimal(?) trade-off between data information and robustness
- flexibility in how we model the tail

$\Longrightarrow$ Further investigation deserved to identify most appropriate model (present results are tentative/illustrative)

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  - inaccurate well-being, but not necessarily "wrong"
  - can be considered not separately from other low extremes (Winsorizing or trimming about 1% in effect makes all incomes positive)
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- In any case, no single best solution: sensitivity checks are relevant (and easy)!

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- Assume upper and/or lower tail follow a given parametric distribution: e.g. Pareto distribution
- Assume a model, but do not restrict “range of data”
- Estimate the model parameters using (robust) techniques
- Either estimate the indicator by combining the ECDF and the model CDF...
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- Assume a model, but do not restrict “range of data”
- Estimate the model parameters using (robust) techniques
- Either estimate the indicator by combining the ECDF and the model CDF...
- ... or simulate from the model to “impute” extreme incomes(controlling for simulation uncertainty)

Technical annex

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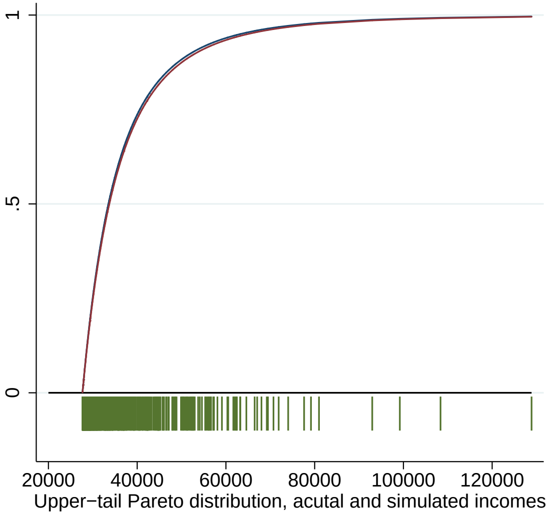

Technical annex

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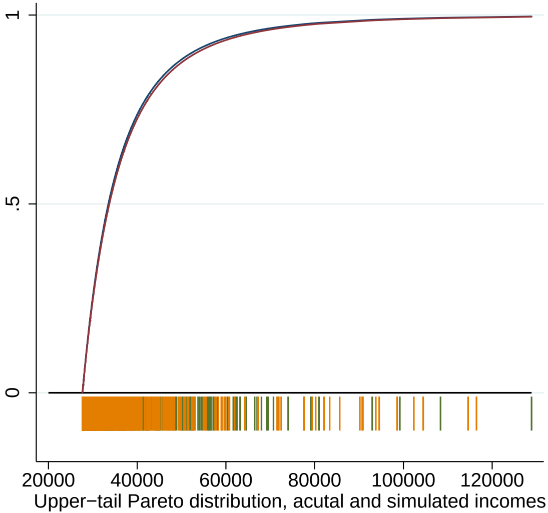

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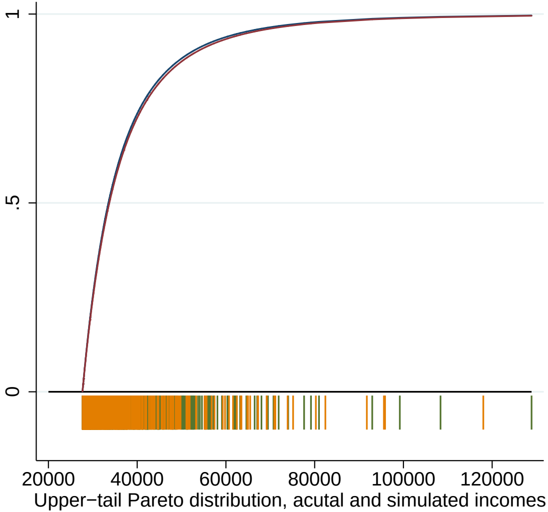

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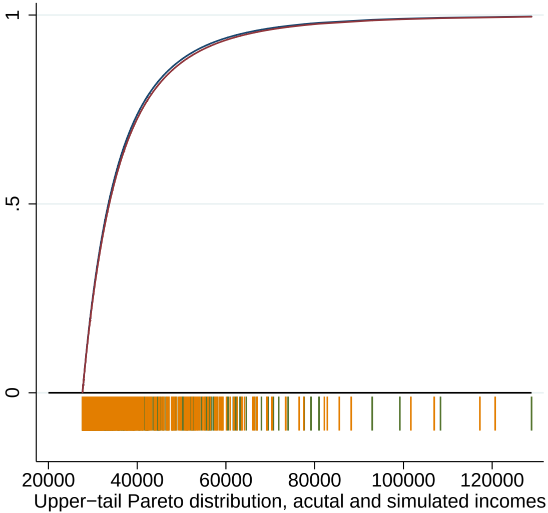

Technical annex

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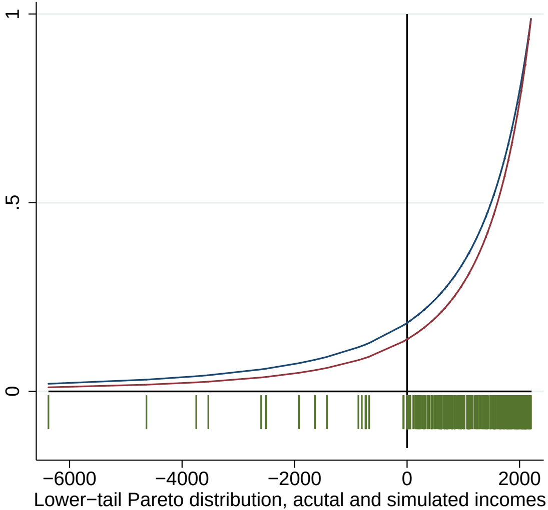

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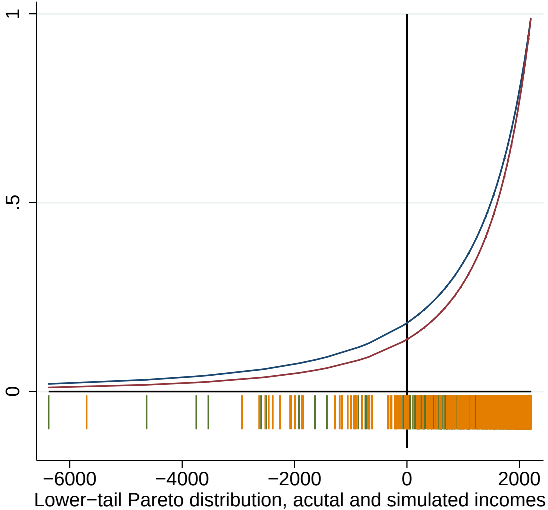

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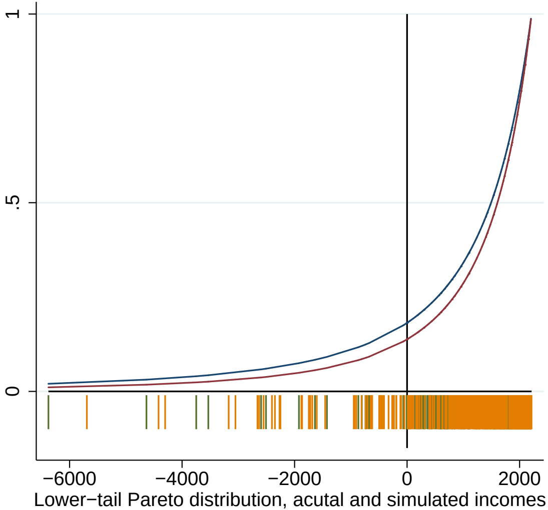

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