The Evolution of Inequality of Opportunity in Germany:
A Machine Learning Approach

Aix-Marseille School of Economics

Econometrics and big data seminar

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Margaret Thatcher

First, that the pursuit of equality itself is a mirage. What's more desirable and more practicable [...] is the pursuit of equality of opportunity.

Speech to the Institute of SocioEconomic Studies
New York, September 15, 1975

Raul Castro

Socialismo significa justicia social e igualdad, pero igualdad de derechos, de oportunidades, no de ingresos.

Speech at the Asamblea Nacional del Poder Popular
La Habana, July 11, 2008

EOp

- equality of opportunity (EOP): a very successful political ideal
- two reasons:
  1. EOP = equality + freedom;
  2. EOP is sufficiently vague.
- contribution: set a standard.

Literature

3 generations of contributions on equality of opportunity:

- theory: Rawls (1971), Dworkin (1981), Arneson (1989) and Cohen (1989), Fleurbaey (1994), Roemer (1998);
- IOP measurement: Lefranc et al. (2009), Checchi and Peragine (2010), Bourguignon et al. (2007), Ferreira and Gignoux (2011);
- econometric specification: Li Donni et al. (2015), Brunori, Hufe and Mahler (2018).

Roemer's Model

$$y_i = g(C_i, e_i)$$

- y_i: individual's i outcome;
- C_i: circumstances beyond individual control;
- e_i: effort.

Types and effort tranches

- Romerian *type*: individuals sharing same circumstances;
- effort *tranche*: individuals exerting the same effort;
- no random component:

$$e_i = e_j \cap C_i = C_j \to y_i = y_j \ , \ \ \forall i, j \in 1, ..., n$$

- equality of opportunity is satisfied if:

$$e_i = e_j \to y_i = y_j \ , \ \ \forall i, j \in 1, ..., n$$

$\Rightarrow$ IOP = within-tranche inequality.

Effort identification

- effort: observable and not observable choices;
- Roemer's identification strategy, two assumptions:
  1. monotonicity: $\frac{\partial g}{\partial e} \geq 0$
  2. orthogonality: $e \perp\!\!\!\perp C$
- degree of effort = quantile of the type-specific outcome distribution;

3-step estimation

1. identification of Romerian types;
2. measurement of degree of effort exerted;
3. (Roemer) IOP = within-tranche inequality

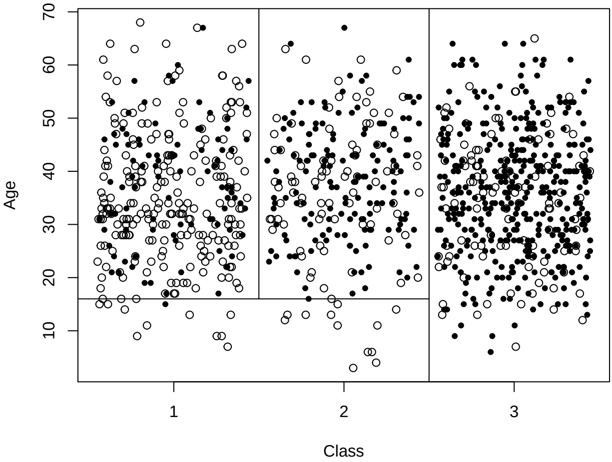
Roemerian types

- two empirical issues of Roemer's theory:
    1. unobservable circumstances (underfitted model);
    2. sparsely populated types (overfitted model).
- bias-variance trade-off $\rightarrow$ downward - upward bias;
- preferred IOP estimates: min MSE.

Romerian types, cnt

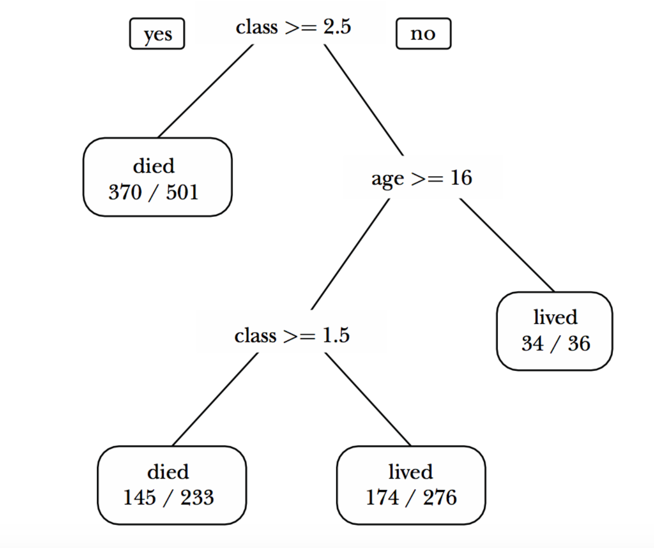
- we use regression tree to identify types;
- partition the space of regressors into non-overlapping regions (Morgan and Sonquist,1963; Breiman et al.,1984)
- the population is divided into non-overlapping subgroups
- prediction of each observation is the the mean value of the dependent variable in the group

What is a tree? cnt.



Source: Varian, 2014

What is a tree? cnt.



Source: Varian, 2014

What is a tree? cnt.

- overfitted models explain perfectly in-sample (high in-sample IOP);
- but perform poorly out-of-sample (low out-of-sample IOP);
- different restrictions to prevent overfitting lead to different types' partition.

Conditional inference trees

- we use *conditional inference trees* (Hothorn et al., 2006);
- splitting are based on a sequence of statistical test;
- Brunori, Hufe, Mahler (2018): outperform standard methods in identifying types.

The algorithm

- choose α
- $\forall p$ test the null hypothesis of independence: $H^{C_p} = D(Y|Cp) = D(Y), \forall C_p \in \mathbf{C}$
- if no (adjusted) p-value $< \alpha \rightarrow$ exit the algorithm
- select the variable, $C^\star$, with the lowest p-value
- test the discrepancy between the subsamples for each possible binary partition based on $C^\star$
- split the sample by selecting the splitting point that yields the lowest p-value
- repeat the algorithm for each of the resulting subsample

Effort

- recall: IOP quantifies to what extent individuals exerting the same degree of effort obtain the same outcome;
- standard approach: choose an arbitrary number of quantiles;
- low efficiency and limited comparability across studies.

Bernstein polynomials

- approximate the ECDF with a polynomial;
- for any quantile $\pi \in [0, 1]$ we can predict the expected outcome in all types;
- we use Bernstein polynomials.

Bernstein polynomials

- Sergei Bernstein (1912)
- mathematical basis for curves' approximation in computer graphics
- outperform competitors (kernel estimators) in approximating distribution functions (Leblanc, 2012)

Bernstein polynomial of degree 4

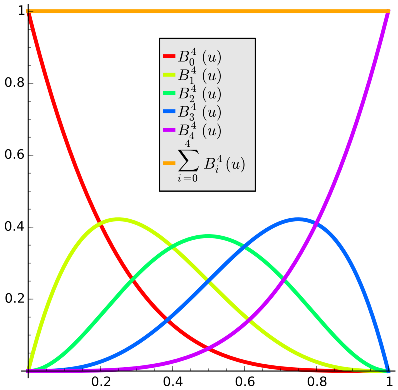
$$B_4(x) = \sum_{v=0}^{4} \beta_v b_{v,4}$$

where β_vs need to be estimated and the Bernstein basis polynomial $b_{v,k}$ is:

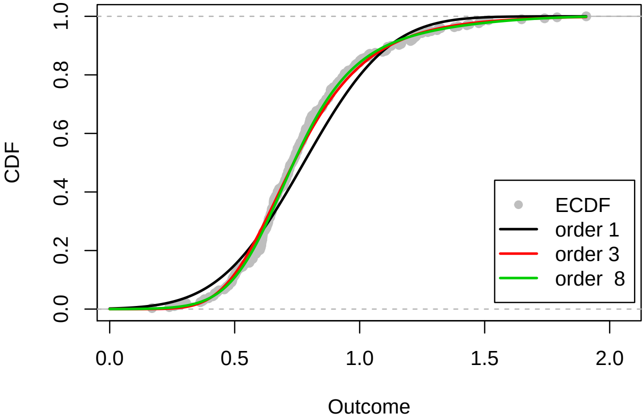
$$b_{v,k} = \binom{k}{v} x^v (1-x)^{k-v}$$

$$\begin{aligned} b_{0,4} &= (1-x)^4 \\ b_{1,4} &= 4x(1-x)^3 \\ b_{2,4} &= 6x^2(1-x)^2 \\ b_{3,4} &= 4x^3(1-x) \\ b_{4,4} &= x^4 \end{aligned}$$

Bernstein polynomials, cnt



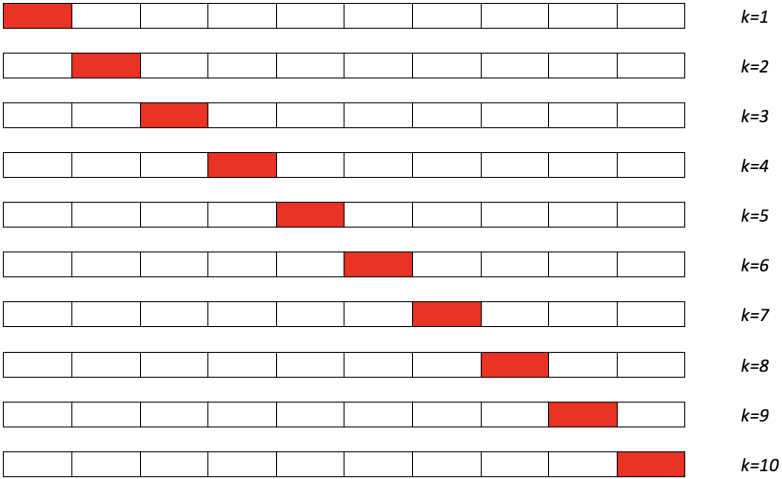
ECDF approximation by Bernstein polynomials



Choice of the polynomial's degree

- the polynomial is estimated with the *mlt* algorithm written by Hothorn (2018);
- out-of-sample log-likelihood to select the most appropriate order of the polynomial;
- out-of-sample log-likelihood is estimated by 10-fold cross validation;

k-fold cross validation



10-fold Cross Validation

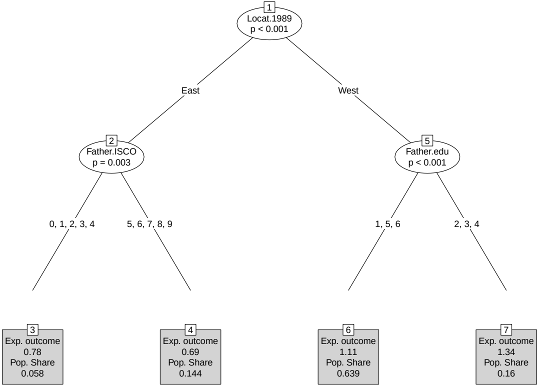
IOP estimation

- Shape of all type-specific distribution functions $\rightarrow$ distribution of EOP violations
- $IOP = Gini\left(\frac{y_i}{\mu_j}\right)$, μ_j expected outcome at percentile j;
- no longer need to choose a particular number of effort quantiles;
- number of quantiles varies to maximize estimate reliability.

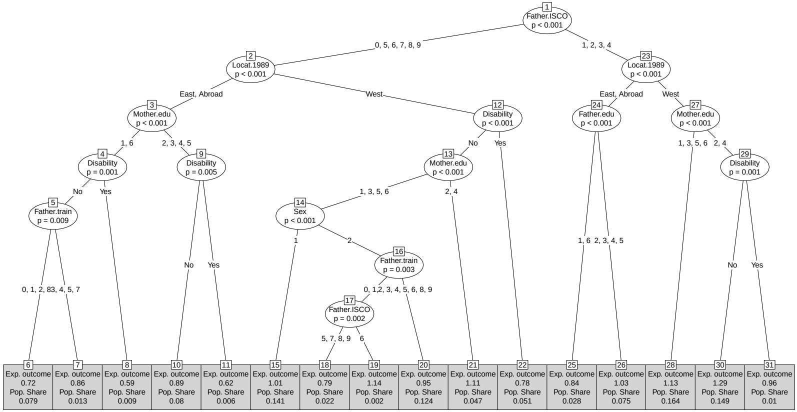
Data

- SOEP (v33) including all subsamples apart from the refugee samples;
- 25 waves 1992-2016;
- adult individuals (30-60);
- circumstances considered: migration background, location in 1989, mother's education, father's education, father's occupation, father's training, month of birth, disability, siblings;
- outcome: 'age-adjusted' household equivalized income

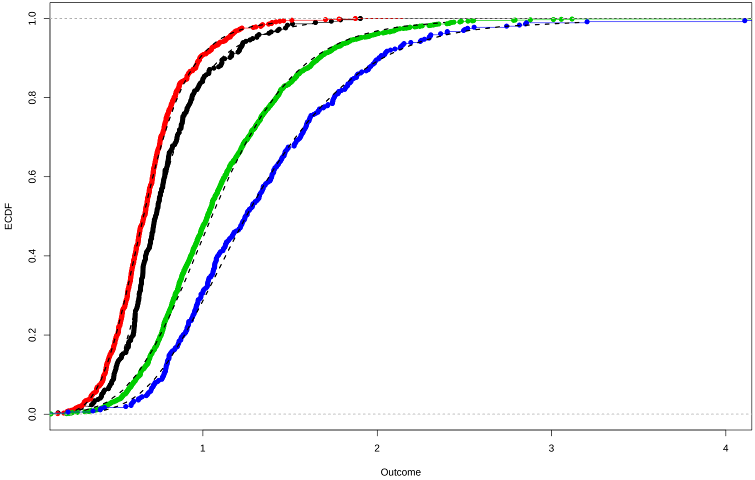
Opportunity tree in 1992



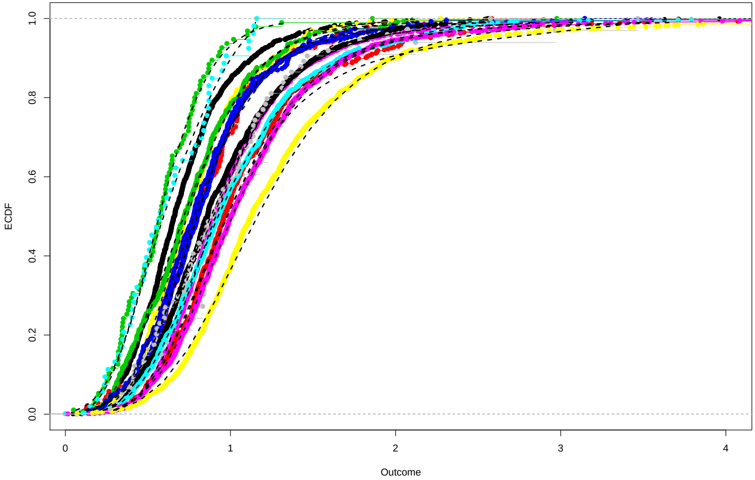
Opportunity tree in 2016



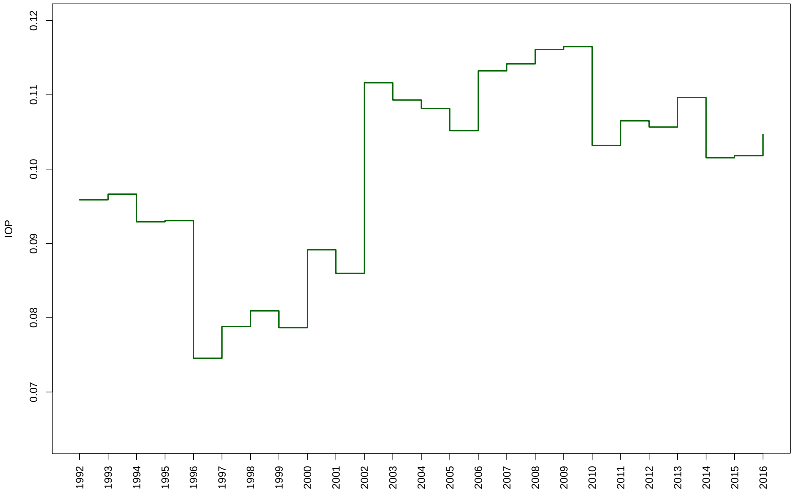
IOP in 1992



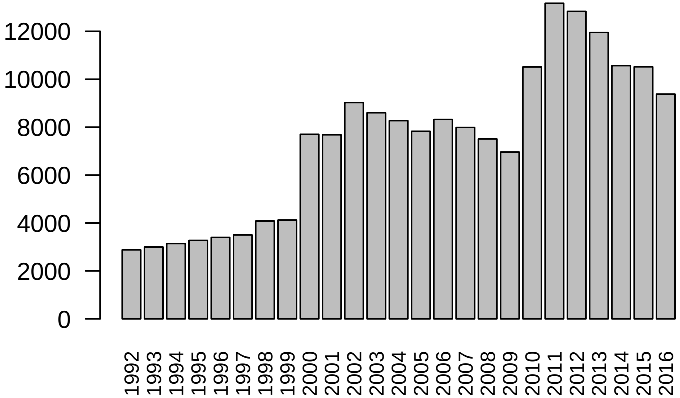
IOP in 2016



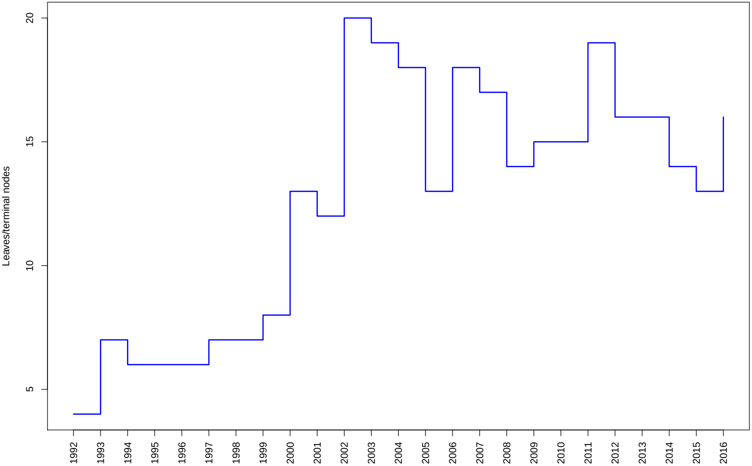
IOP trend 1992-2016



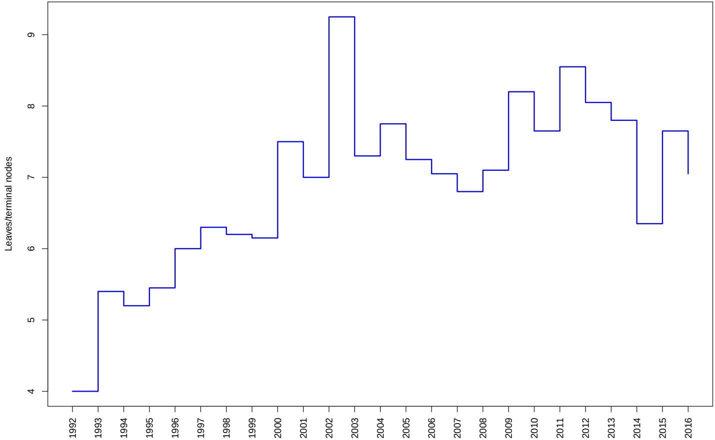
Sample size 1992-2016



Number of types 1992-2016



Mean number of types (same sample size) 1992-2016



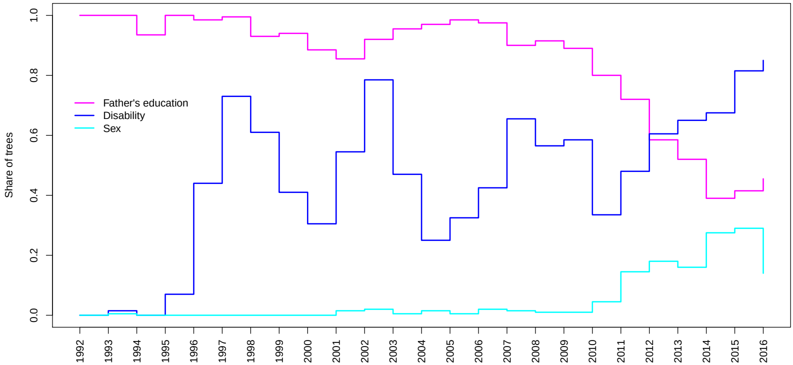
Mean IOP trend 1992-2016 (same sample size)

Confidence bounds are the 0.975 and 0.025 quantiles of the distribution of IOP estimates.

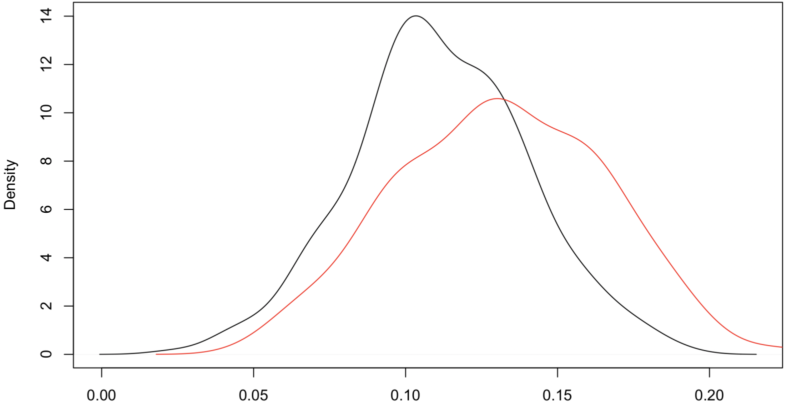
Summary

- wan approach to estimate IOP fully consistent to Roemer's theory;
- effort identification method maximizes efficiency and comparability;
- since 1992 in Germany the opportunity structure has become more complex;
- IOP declined after reunification and increased with *Hartz reforms*;
- is today about 10% higher than in 1992.

Share of trees that use fathers education, disability and sex to obtain Romerian type



Distribution of bootstrap estimates



Mother/father raining

mtraining / ftraining

cod.	Berufsbildung M/V	Vocational Training M/F
1	Keine Ausbildung	No vocational degree
2	Berufliche Ausbildung	Vocational Degree
3	Gewerbliche oder Landwirtschaftliche Leh	Trade or Farming Apprentice
4	Kaufm.L.,Bfs,Handel	Business
5	Gesundheitswesen, FS,Techn.-o.Meisters	Health Care or Special Technical School
6	Beamtenausbildung	Civil Service Training
7	FHS,Ingeniuerschule	Tech Engineer School
8	Hochsch.,Universit. (In- und Ausland)	College, University (in GER or Abroad)
9	Sonstige Ausbildung	Other Training

Mother/father education

fsed / msed

cod.	Schulbildung Vater / Mutter	Father/Mother Education
1	[1] Hauptschule	Lower Secondary
2	[2] Realschule	Intermediate Secondary
3	[3] Fachoberschule	Technical School
4	[4] Abitur	Upper Secondary
5	[5] sonstiger Abschluss	Other School Degree
6	[6] Kein Abschluss	No School Degree
7	[7] Keine Schule besucht	School not attended