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

8^{th} ECINEQ Meeting
Paris School of Economics - July 3-5, 2019

Paolo Brunori
University of Florence & University of Bari

Guido Neidhöfer
ZEW

Motivation

"Most of the empirical literature continues to treat [ex-ante and ex-post approaches] as interchangeable, by motivating their concern with inequality of opportunity from ex-post intuitions and using ex-ante measures of inequality of opportunity."

Ramos and Van de Gaer, 2019

Literature

- a "third generation" paper on inequality of opportunity:
- first generation (theory): moral philosophers and welfare economists Rawls (1971), Dworkin (1981), Arneson (1989) and Cohen (1989), Roemer (1998);
- second generation (measurement): Lefranc et al. (2009), Checchi and Peragine (2010), Bourguignon et al. (2007), Ferreira and Gignoux (2011);
- third generation (ex-ante econometric specification): Li Donni et al. (2015), Brunori et al. (2018)

Roemer's Model

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

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

Types and effort tranches

- Romerian type: set of individuals sharing exactly the same circumstances;
- effort tranche: set of individuals exerting the same effort;
- there is equality of opportunity if:

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

$\Rightarrow$ IOP = within-tranche inequality.

Effort identification

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

3-step estimation

- identification of Romerian types;
- measurement of degree of effort exerted;
- IOP $= I\left(\frac{y_i}{\mu_j}\right),\ \mu_j = \mathbf{E}[y|_e]$

Roemerian types

- conditional inference trees (Hothorn et al., 2006);
- algorithm to predict a dependent variable partitioning a controls' space into non-overlapping regions;
- Brunori, Hufe, Mahler (2018): outperform standard methods to identify types in terms of out-of-sample MSE.

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

- standard approach: choose an arbitrary number of quantiles;

- limited comparability across studies;

- our approach: Bernstein polynomial approximation.

Bernstein polynomials

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

Bernstein polynomial of degree 4

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

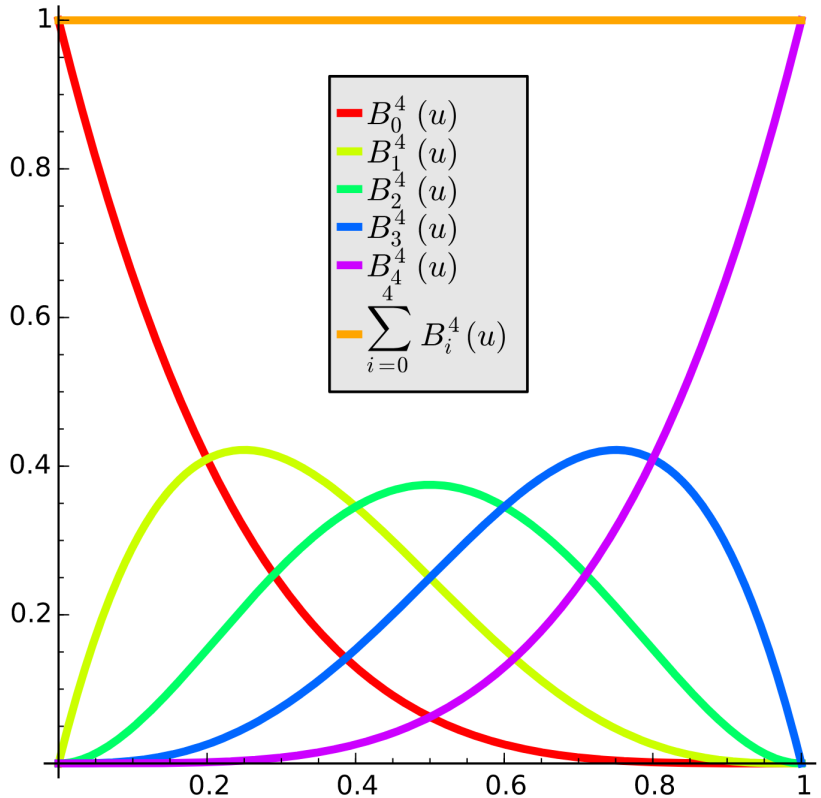
where $\beta_v b_{v,4}$ is the v-th Bernstein basis polynomial

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

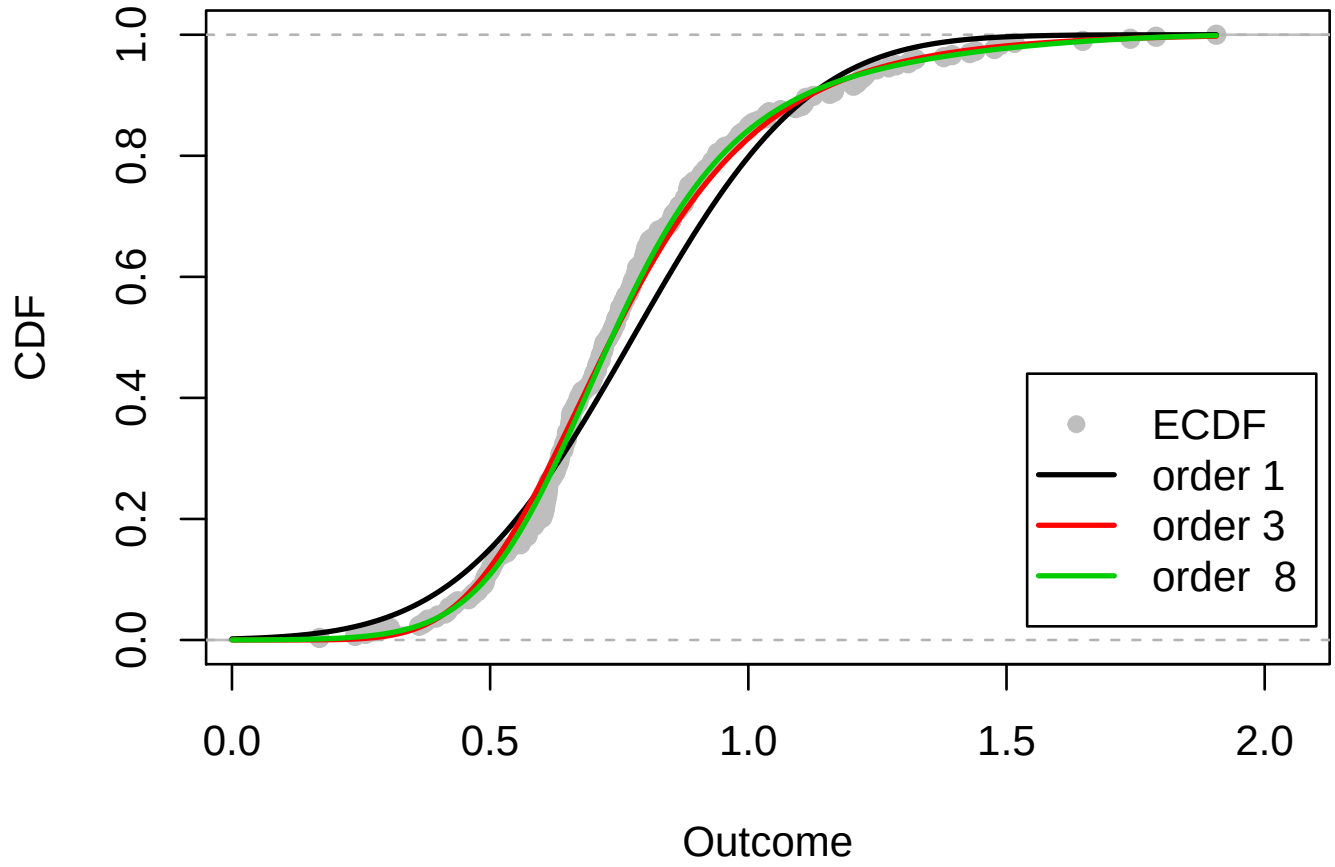
example

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

Bernstein polynomials, cnt



ECDF approximation by Bernstein polynomials



Choice of the polynomial's degree

- out-of-sample log-likelihood to select the most appropriate order of the polynomial;
- out-of-sample log-likelihood is estimated by 5-fold cross validation;
- the polynomial is estimated with the *mlt* algorithm written by Hothorn (2018).

IOP in Germany

- SOEP (v33) including all subsamples apart from the refugee samples;
- adult individuals (30-60);
- $y =$ age-adjusted household equivalent disposable income;
- $IOP = Gini\left(\frac{y_i}{\mu_j}\right)$, $\mu_j =$ tranche avg.

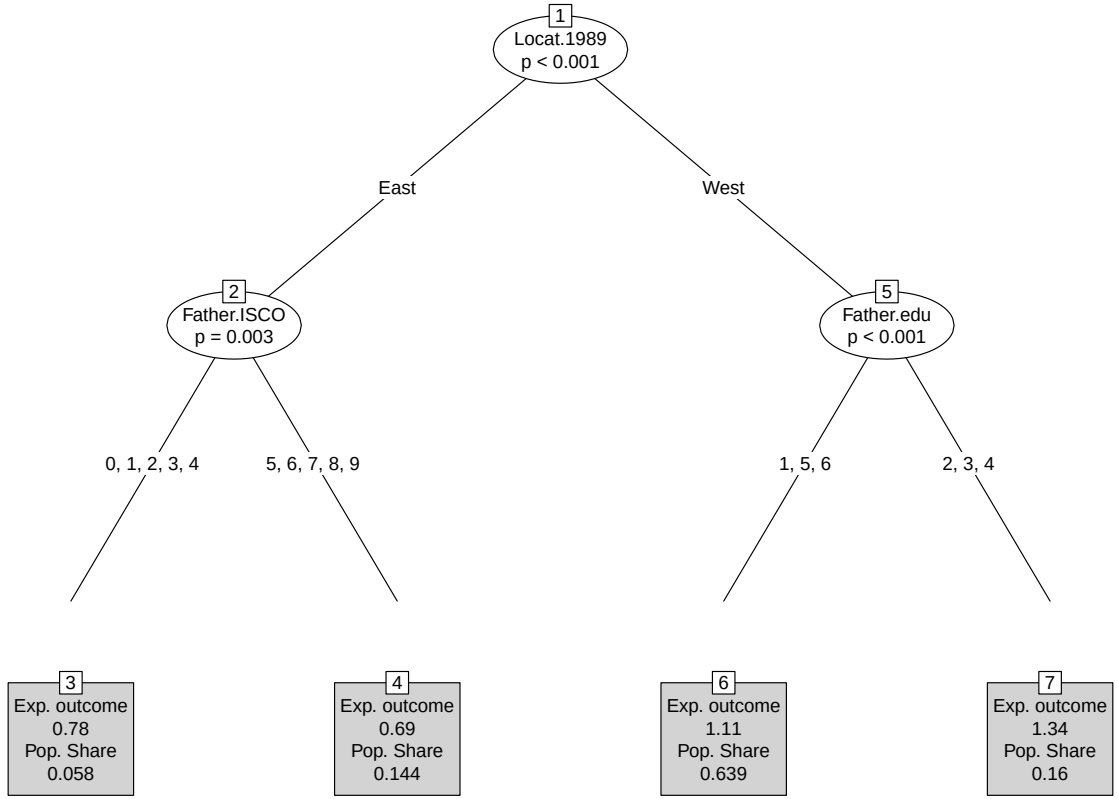
Missing information about circumstances

- SOEP provides comprehensive information about circumstances beyond individual control;

- waves considered 1992-2016;

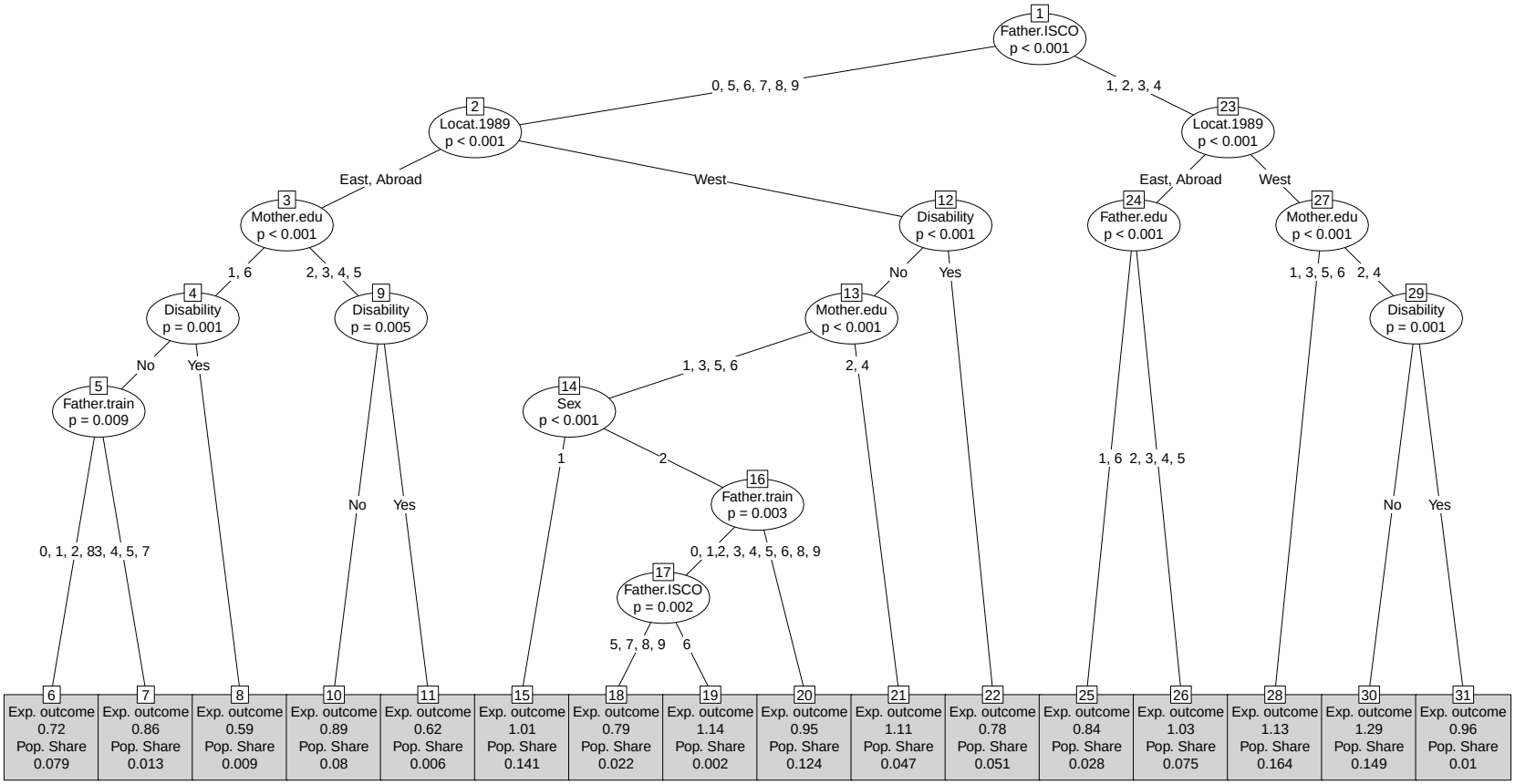
- circumstances considered: migration background, location in 1989, mother's education, father's education, father's occupation, father's training, disability, siblings;

Opportunity tree in 1992



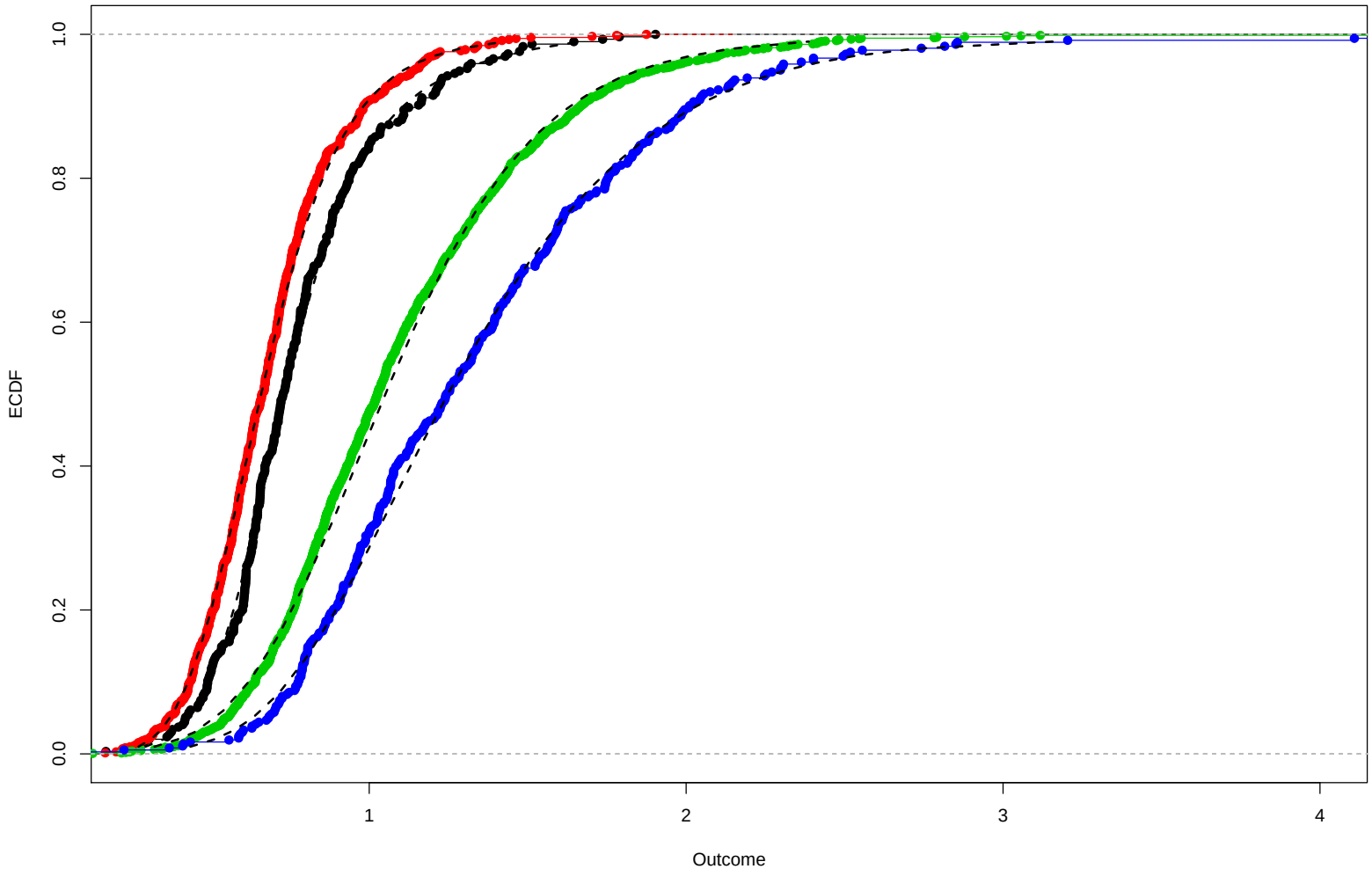
Edu: 1=Sec., 2=Interm., 3=Tech., 4=Upper sec., 5=Other degr., 6=No degr., 7=Not atteded

Opportunity tree in 2016

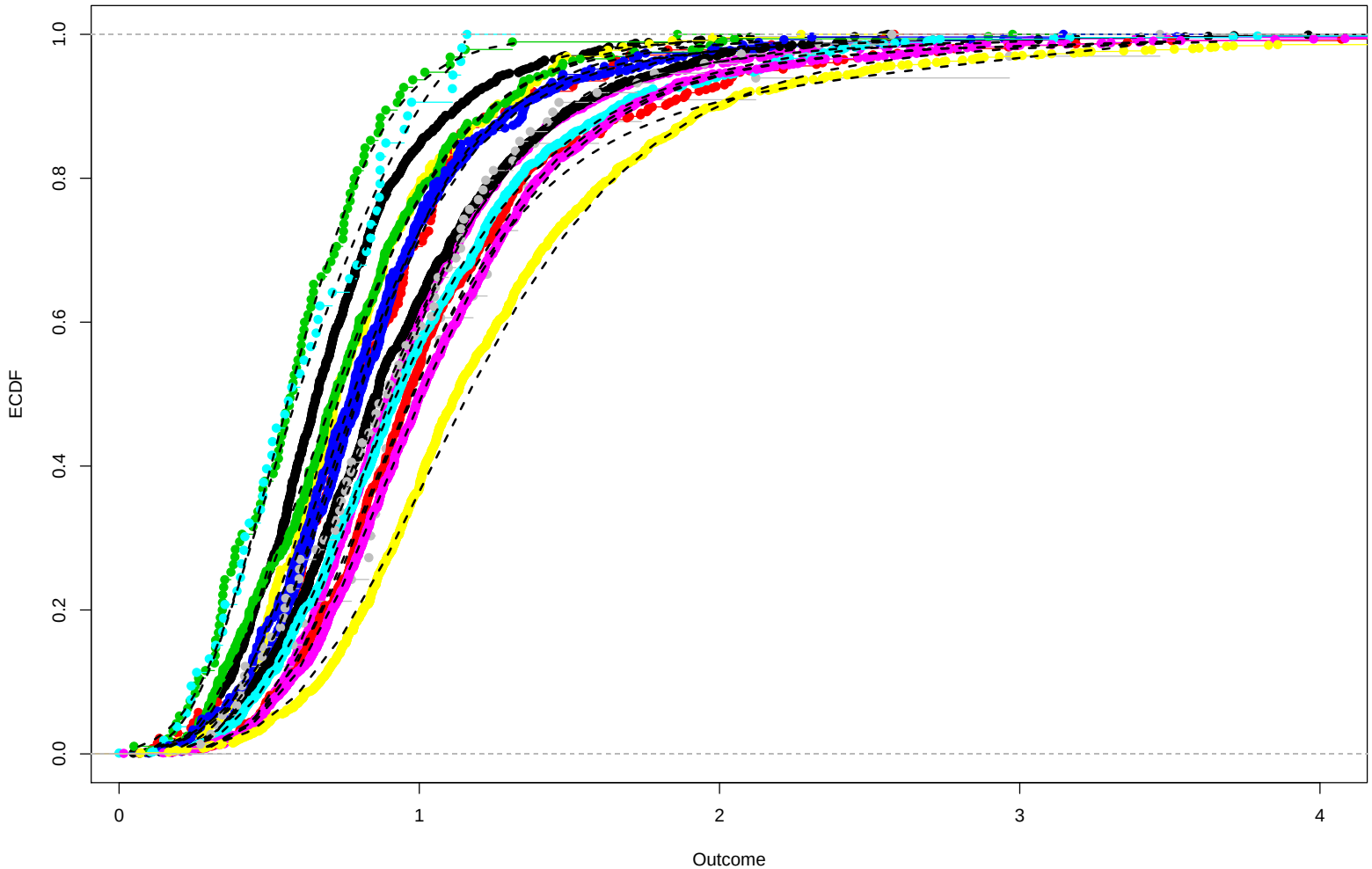


Edu: 1=Sec., 2=Interm., 3=Tech., 4=Upper sec., 5=Other degr., 6=No degr., 7=Not atteded

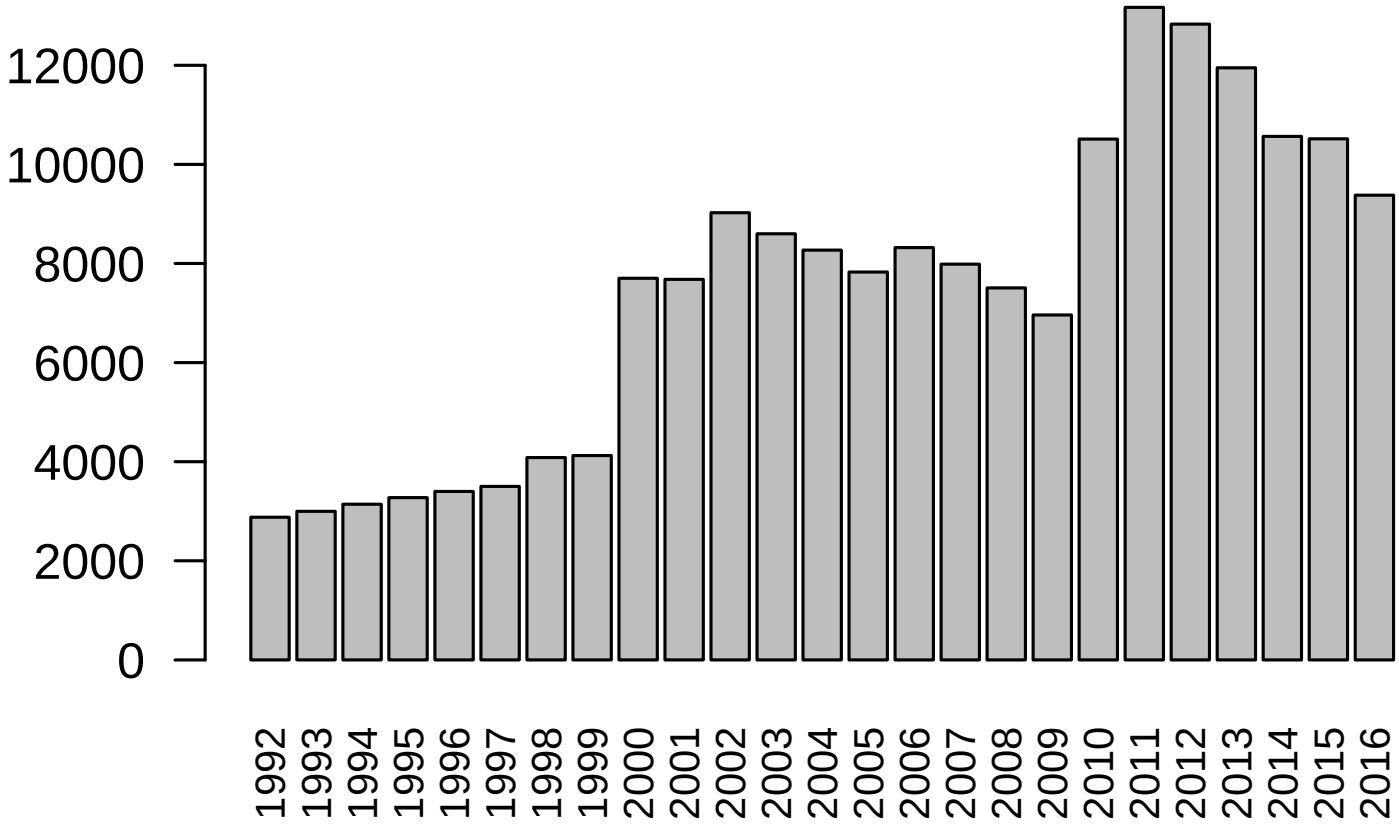
IOP in 1992



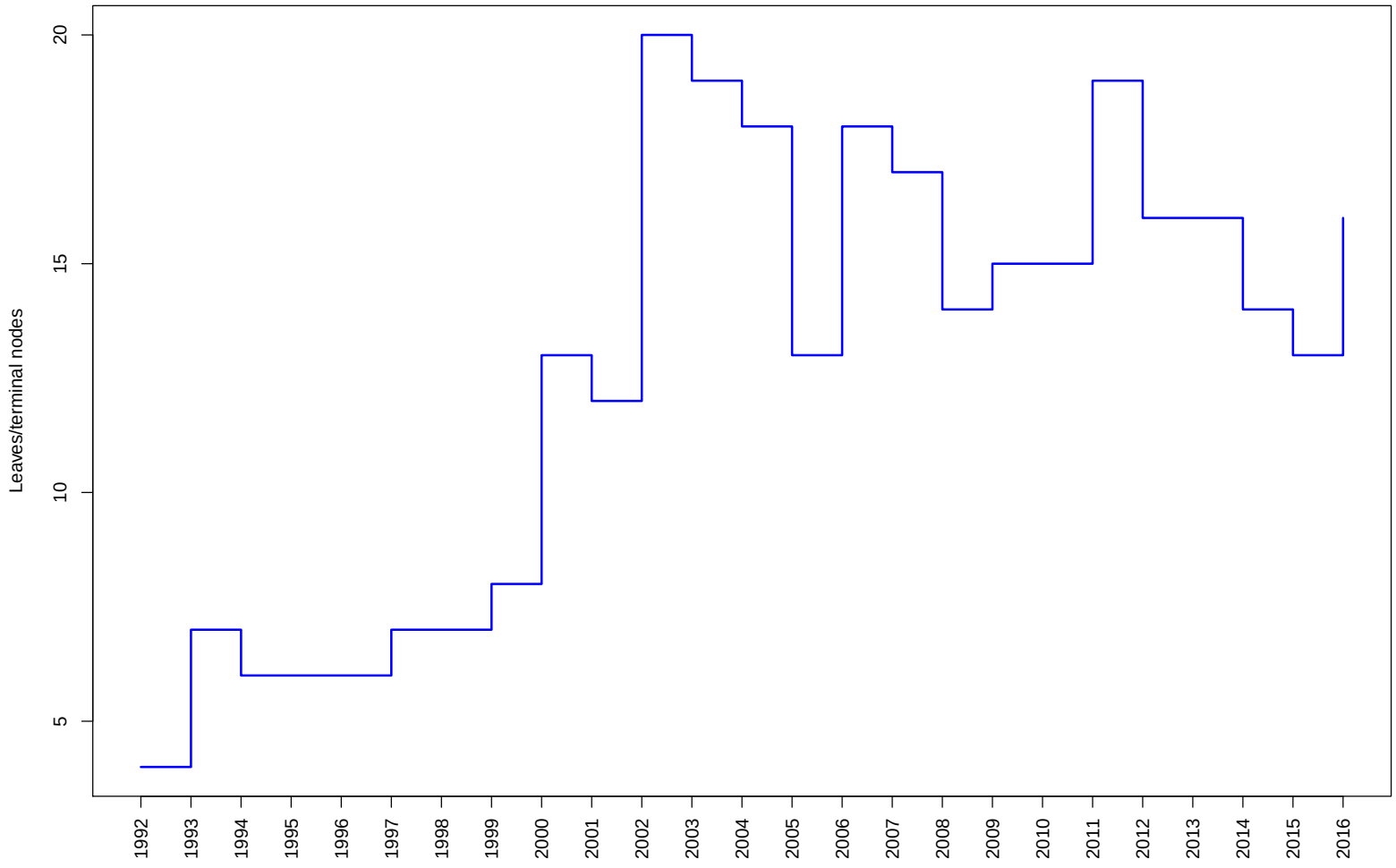
IOP in 2016



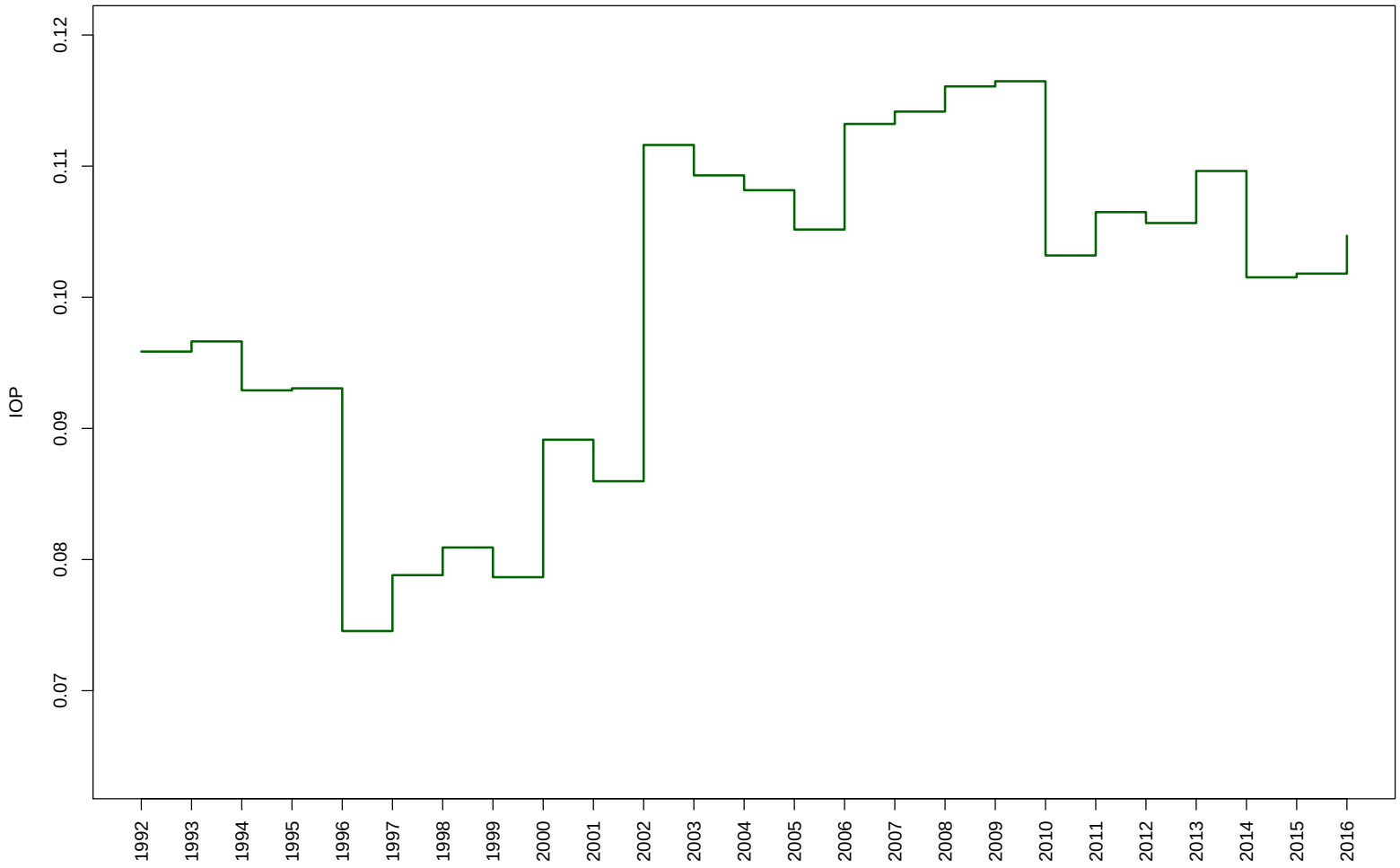
Sample size 1992-2016



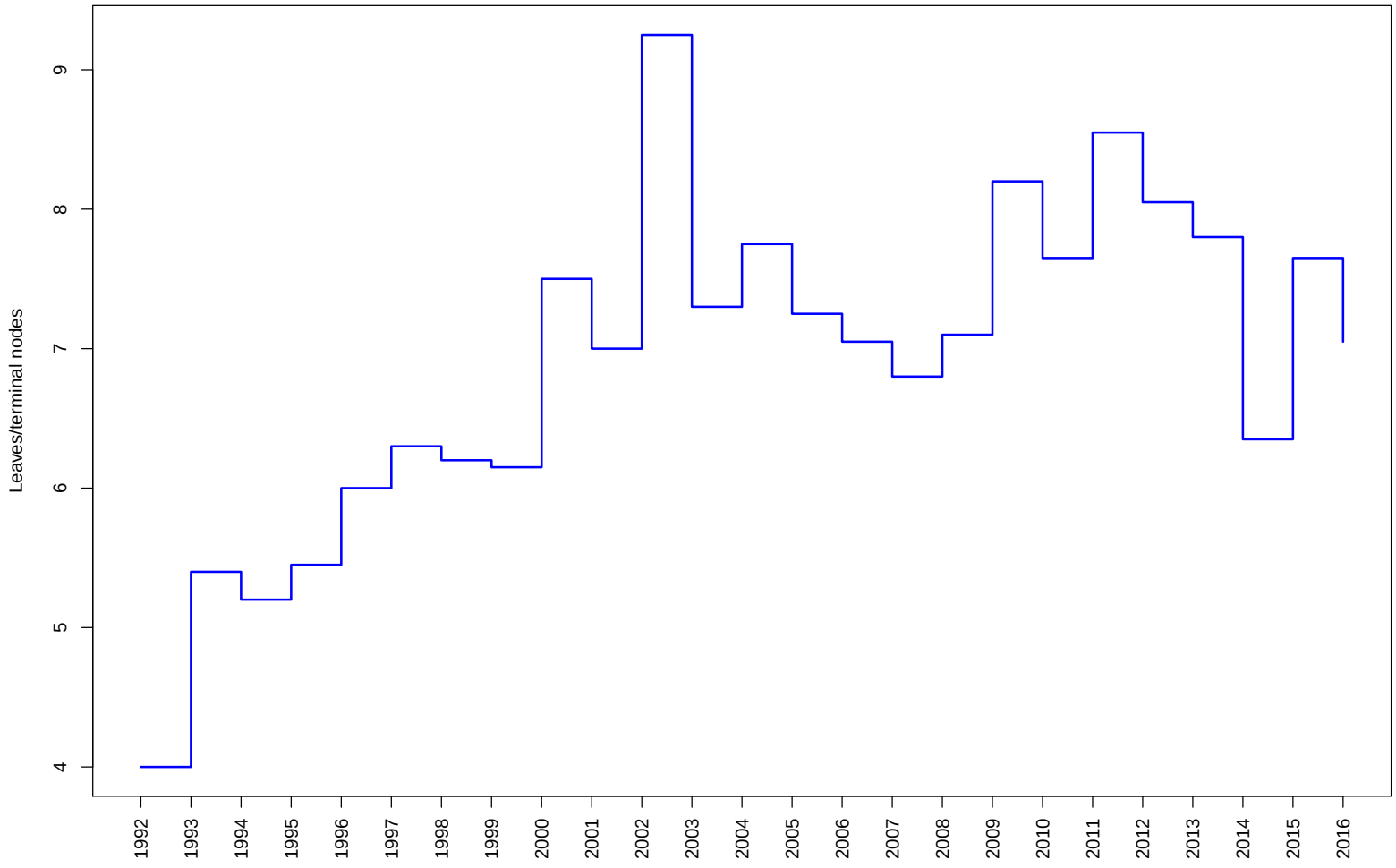
Types 1992-2016



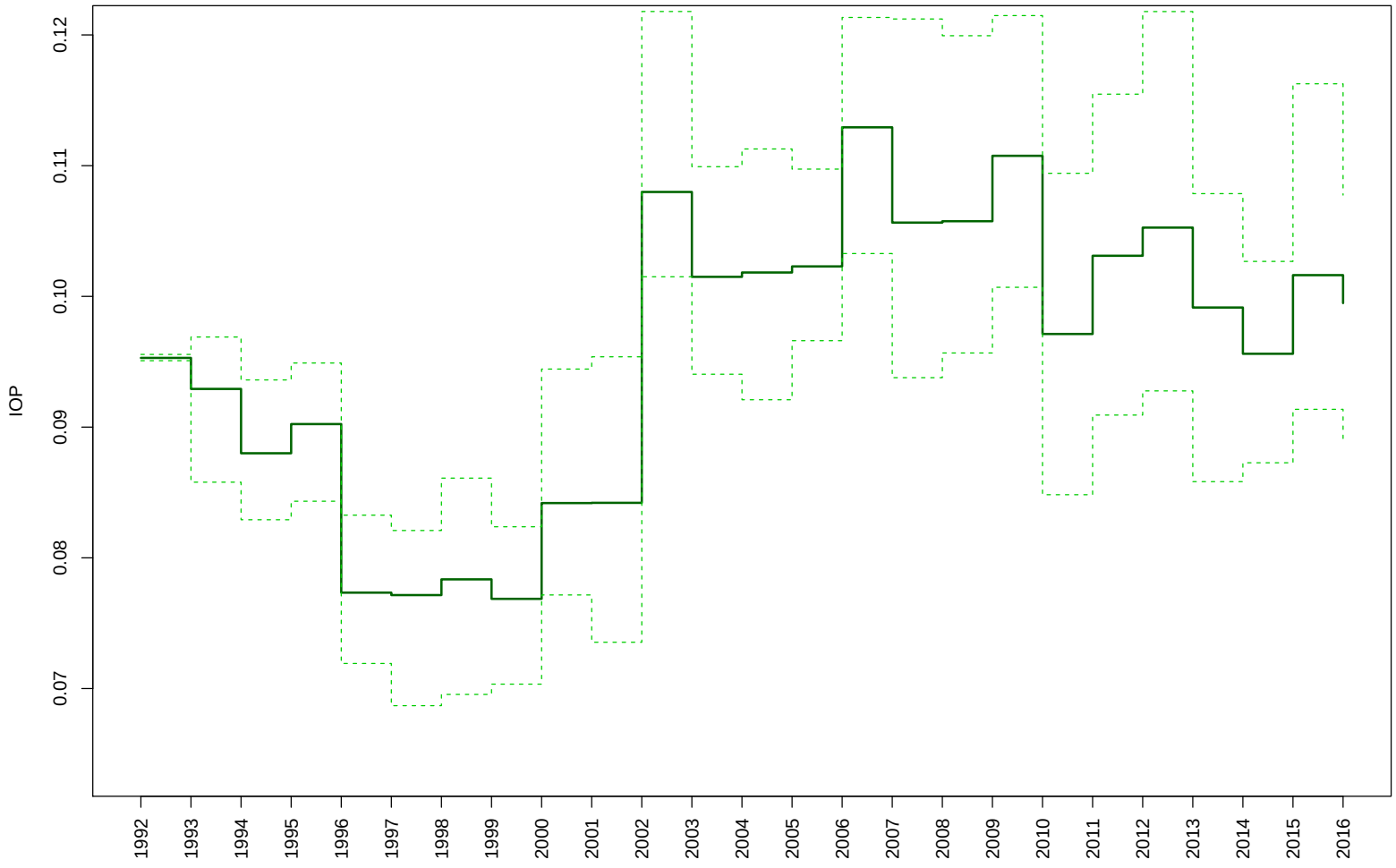
IOP trend 1992-2016



Types 1992-2016 (same sample size)



IOP trend 1992-2016 (same sample size)



Summary

- our effort identification method maximizes comparability;
- same approach may be used with observable 'efforts';
- since 1992 in Germany the opportunity structure has become more complex;
- IOP declined after reunification and surged in early '00s (*hartz reforms*);
- $IOP_{1992} \approx IOP_{2016}$