Model-Based Recursive Partitioning to Estimate Unfair Health Inequalities in the United Kingdom Household Longitudinal Study

London School of Economics, III Seminar

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III - London School of Economics

This project

- co authored with Apostolos Davillas, Andrew M. Jones and Giovanna Scarchilli;
- model-based recursive partitioning algorithm to estimate health inequalities;
- evidence from the UK Household Longitudinal Study.

Health inequalities

"Health inequities are differences in health status [..] between different population groups, arising from the social conditions in which people are born, grow, live, work and age. Health inequities are unfair and could be reduced by the right mix of government policies."

World Health Organization, 2018

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Responsibility-egalitarianism in health

- Moral philosophy and distributive justice theory: Rawls(1958, 1971), Sen (1980), Cohen (1989); Dworkin (1981); Fleurbaey (2008);

- Formalized by Fleurbaey and Shocckaert (2009) for health but rarely implemented;

- Parallel to the literature on inequality of opportunity in health (Roemer, 1998; Rosa Dias, 2009; Jusot et al., 2013; Li Donni et al., 2015; Carrieri and Jones, 2018; Carrieri et al., 2020; Davilas and Jones, 2020).

Responsibility-egalitarianism in health

Alcohol abusers should not get transplants, says Best surgeon

- **Liver shortage means help should be more targeted**
- **Support needed to stop relapses into drinking**

The surgeon who performed George Best's liver transplant says urgent measures are needed to identify patients who are likely to abuse alcohol after their operations, so they can be kicked off hospital waiting lists.

Source: Gurdian, 5th Oct. 2005

Responsibility-egalitarianism in health

HUFFPOST
IN COLLABORAZIONE CON GEDI

POLITICA 31/08/2021 08:11 CEST | **Aggiornato** 31/08/2021 10:22 CEST

"I No Vax si paghino le cure". Il piano della Regione Lazio, dubbi sulla fattibilità

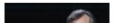
L'assessore D'Amato: "Se finiscono in terapia intensiva si dovranno pagare il ricovero". Che costa 1.500 euro al giorno

HuffPost

TENDENZE

Padre senza green pass in una scuola a Bergamo: "Portatemi i figli o chiamo i carabinieri"

Gustavo Zagrebelsky: "Non è libertà ma arbitrio. La lotta no vax è una forma di prepotenza" (di F. Fantozzi)



"Pericolosissime bugie"

Source: HuffingtonPost Italia, 31.08.2021

Model

$$h = f(\mathbf{C}, E, D) + \epsilon$$

types: individuals sharing same circumstances;

effort tranches: individuals sharing same lifestyle.

Model, example

		SMOKE					
RACE	GENDER	> 20	10-20	5-10	1-5	ex	never
white	male	$h_1^{1,1}$	$h_2^{1,2}$	$h_3^{1,3}$	$h_4^{1,4}$	$h_5^{1,5}$	$h_6^{1,6}$
white	female	$h_7^{2,1}$	$h_8^{2,2}$	$h_9^{2,3}$	$h_{10}^{2,4}$	$h_{11}^{1,5}$	$h_{12}^{1,6}$
black	male	$h_{13}^{3,1}$	$h_{14}^{3,2}$	$h_{15}^{3,3}$	$h_{16}^{3,4}$	$h_{17}^{1,5}$	$h_{18}^{1,6}$
black	female	$h_{19}^{4,1}$	$h_{20}^{4,2}$	$h_{21}^{4,3}$	$h_{22}^{4,4}$	$h_{23}^{1,5}$	$h_{24}^{1,6}$

Fleurbaey and Schokkaert's UI

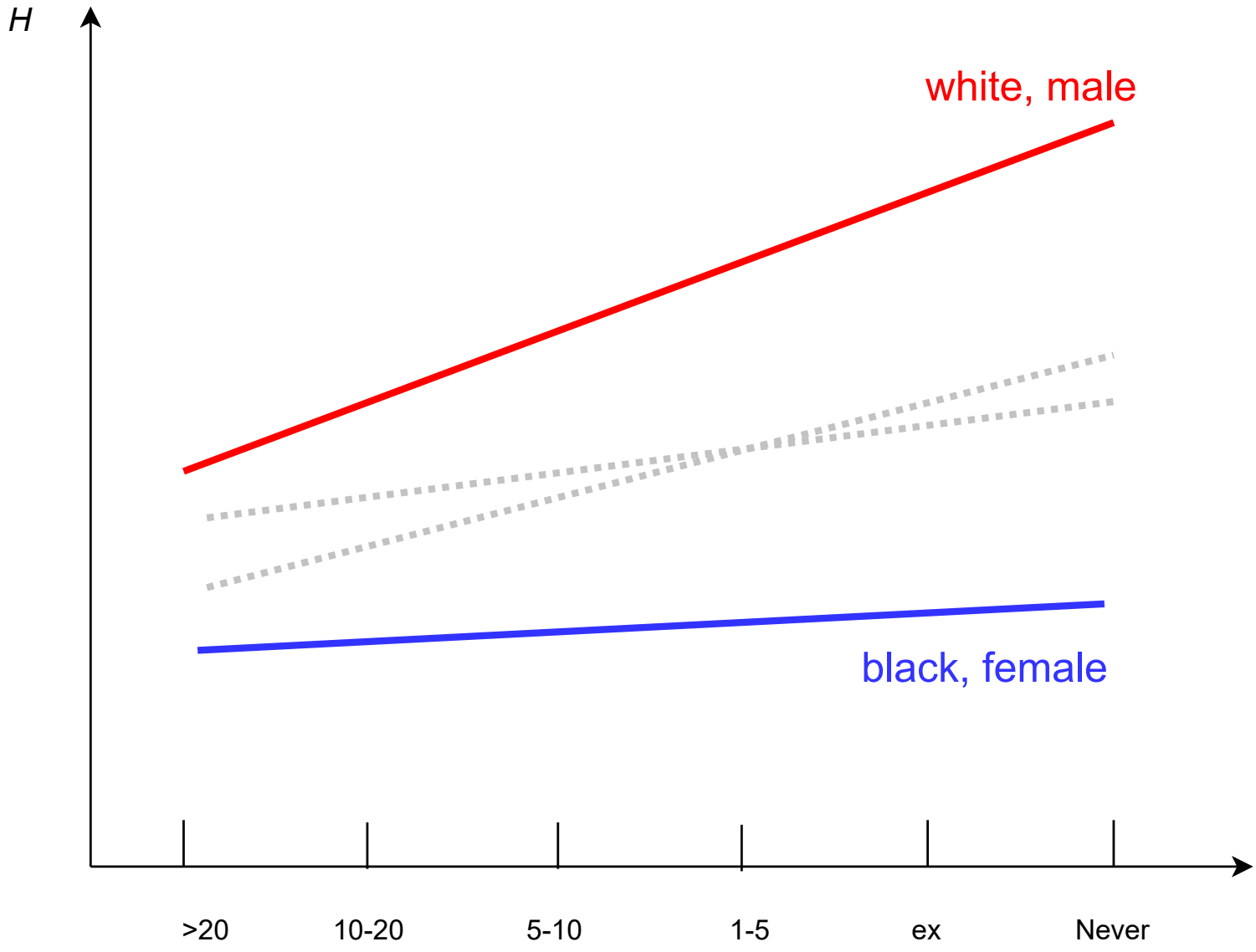
UI is inequality in $\tilde{H}$, obtained fromn H so that:

- $\tilde{H}$ does not contain any legitimate variation in H (*Reward principle)*;

- $\tilde{H}$ does contain all illegitimate differences in H (*Compensation principle*).

Fleurbaey (2008): unless DGP is additive separable the two principles are incompatible.

Model, example



Direct unfairness and fairness gap

- $\tilde{H}_{DU}$: replace individual $h_i^{k,j}$ with $\mathbb{E}\left[g(C_k, \tilde{E})\right]$
- $\tilde{H}_{FG}$: replace individual $h_i^{k,j}$ with $h_i^{k,j} - \mathbb{E}\left[g(\tilde{C}, E_j)\right]$
- where $\tilde{E}$ and $\tilde{C}$ are reference tranche and reference type;

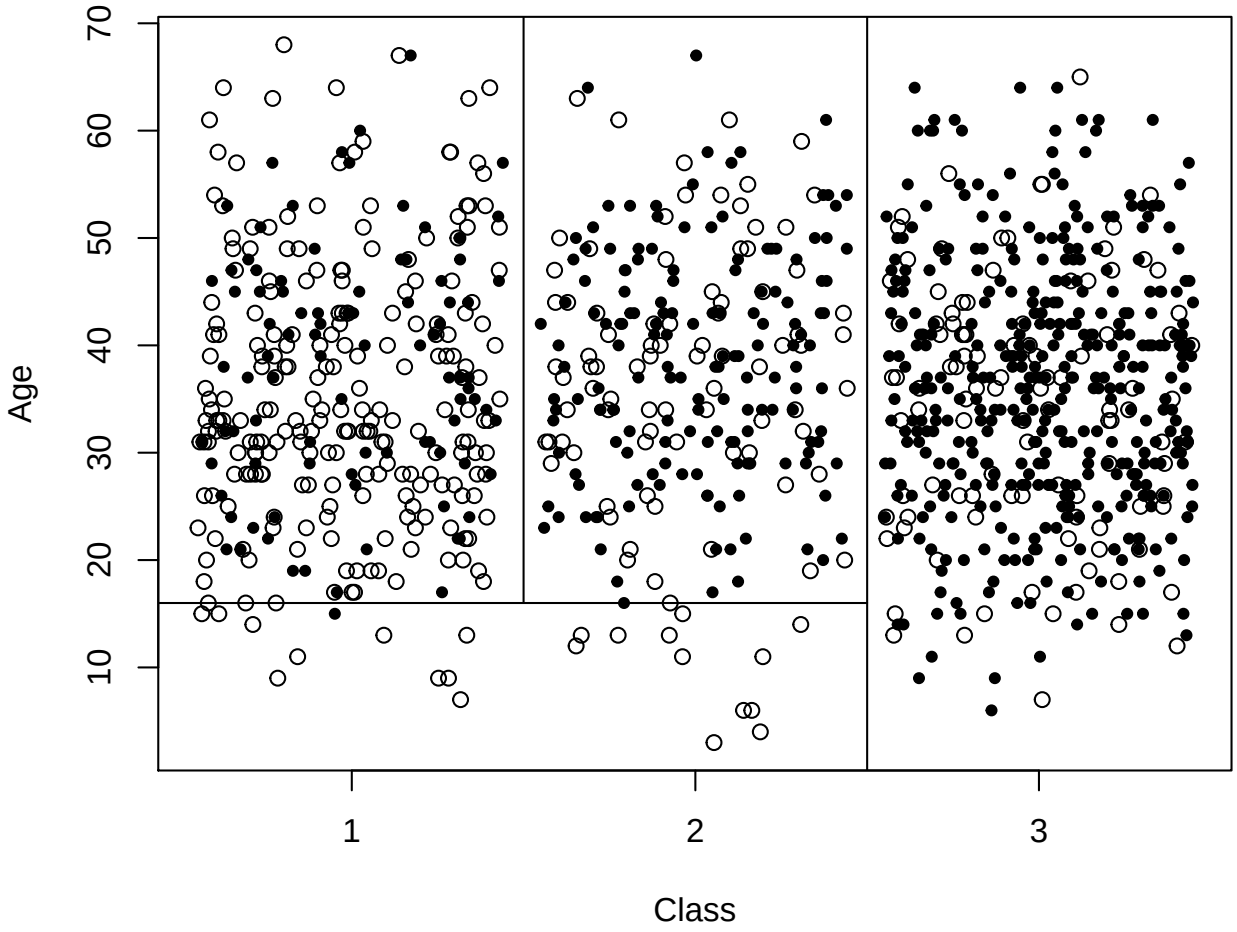
Types' identification

- Previous contributions: arbitrary identification of types (e.g. Rosa Dias, 2009; Jusot et al., 2013);

- recently: latent class model (Li Donni et al., 2015; Carrieri and Jones, 2018), regression trees and forests (Brunori, Hufe, Mahler, 2018);

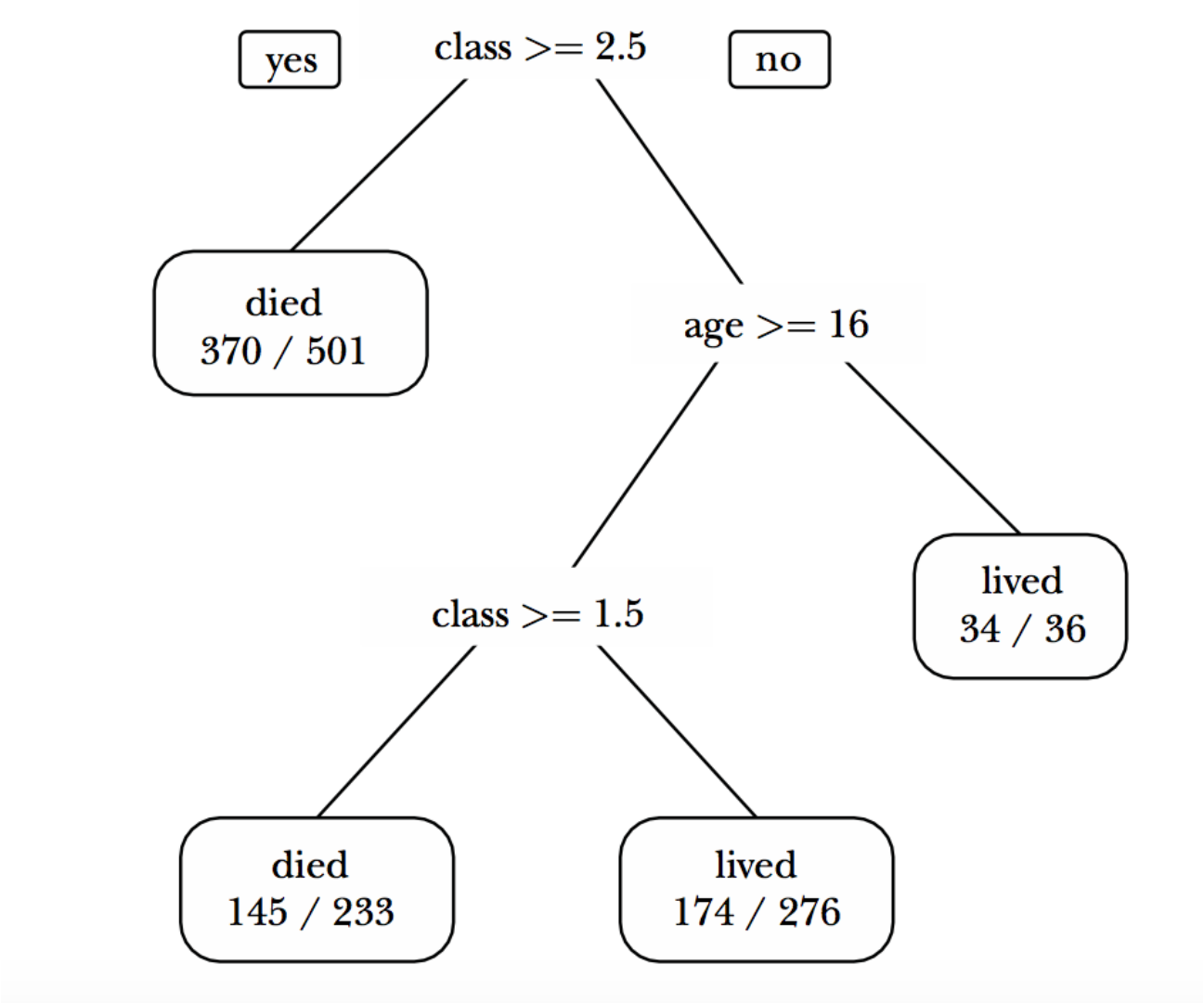
- our proposal: Model-based recursive partitioning (MOB) (Zeileis et al., 2008).

From tree to MOB



Source: modified but originally in Varian (2014)

From tree to MOB, cnt.

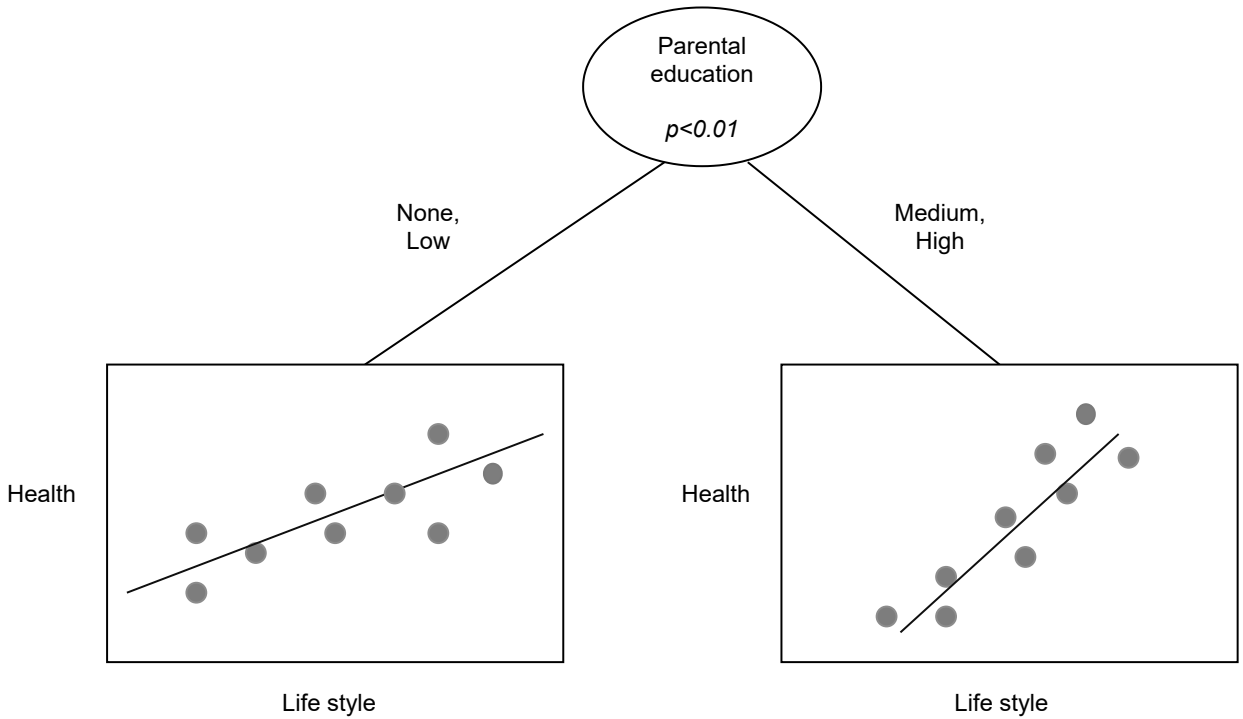


Source: Varian, 2014

MOB algorithm

1. a confidence level is set $(1 - \alpha)$;
2. a model is fitted in the entire sample $(h = \beta_0 + \beta_1 E + u)$;
3. a M-fluctuation test is performed on the stability of the parameters depending on realization of $c \in \mathbf{C}$;
4. If H_0 is rejected a split is performed, otherwise the algorithm stops;
5. repeat 2-5 on the resulting sub-samples.

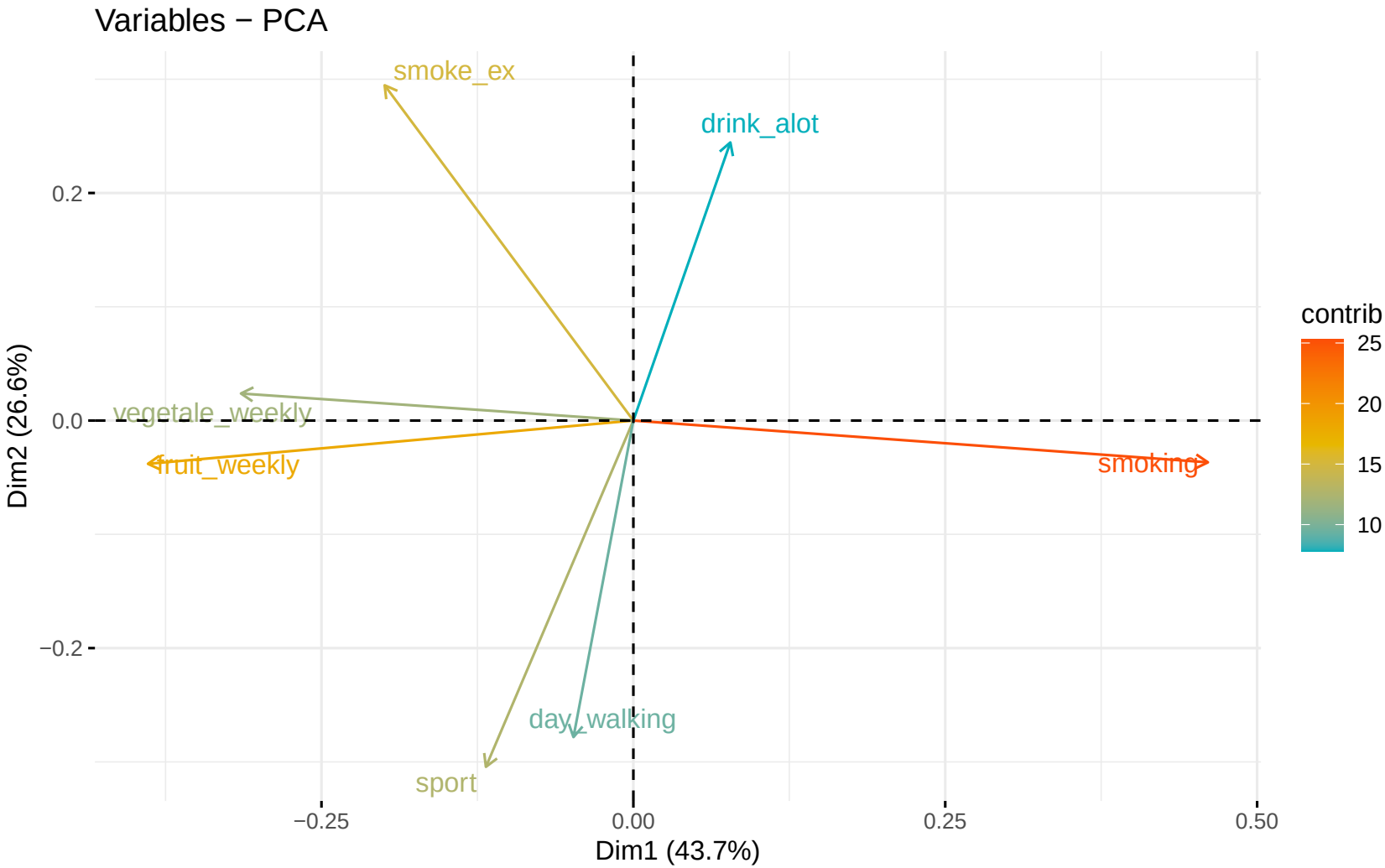
MOB output


Parental
education
p<0.01
None,
Low
Medium,
High
Health
Health
Life style
Life style

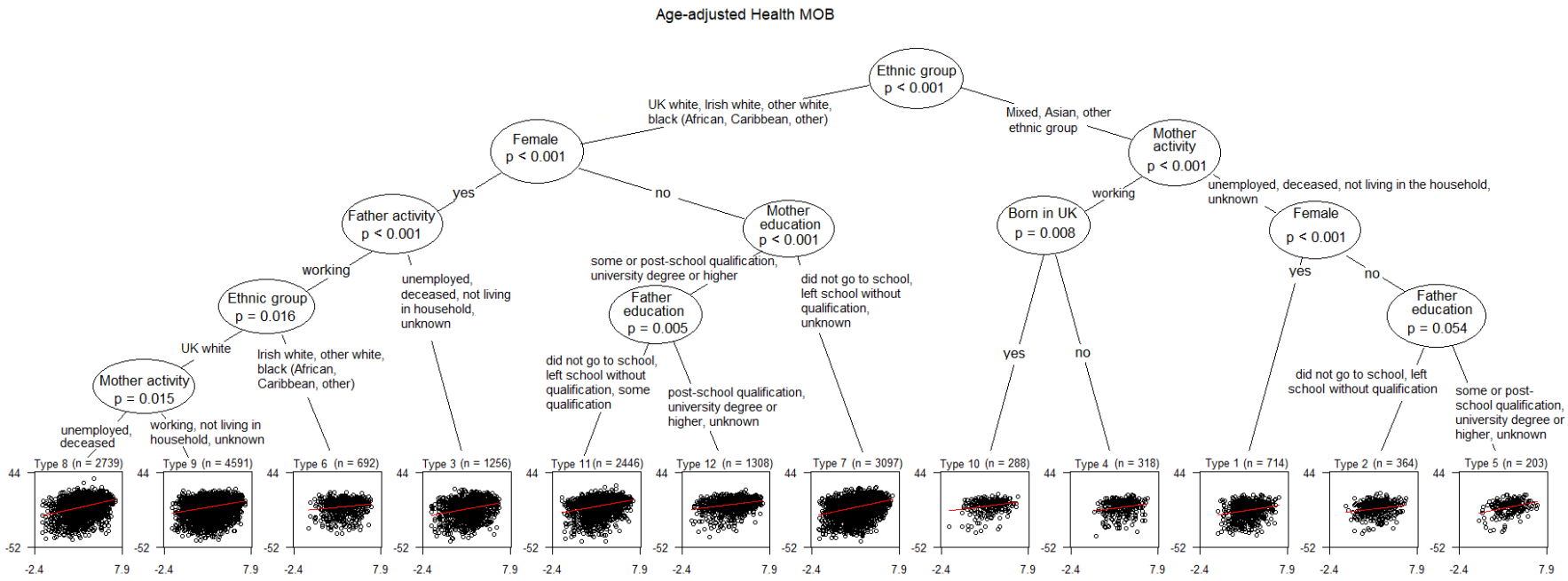
Data

- UK Household longitudinal Survey;
- health outcome: Physical Component Score of the SF-12 score in wave 6 (2014-16);
- circumstances: gender, ethnicity, parental education and parental occupation (age 14);
- lifestyle variables: diet (fruit/vegetables), smoking, sport, sedentary life in wave 2 and 5 (2010-12 and 2013-15).

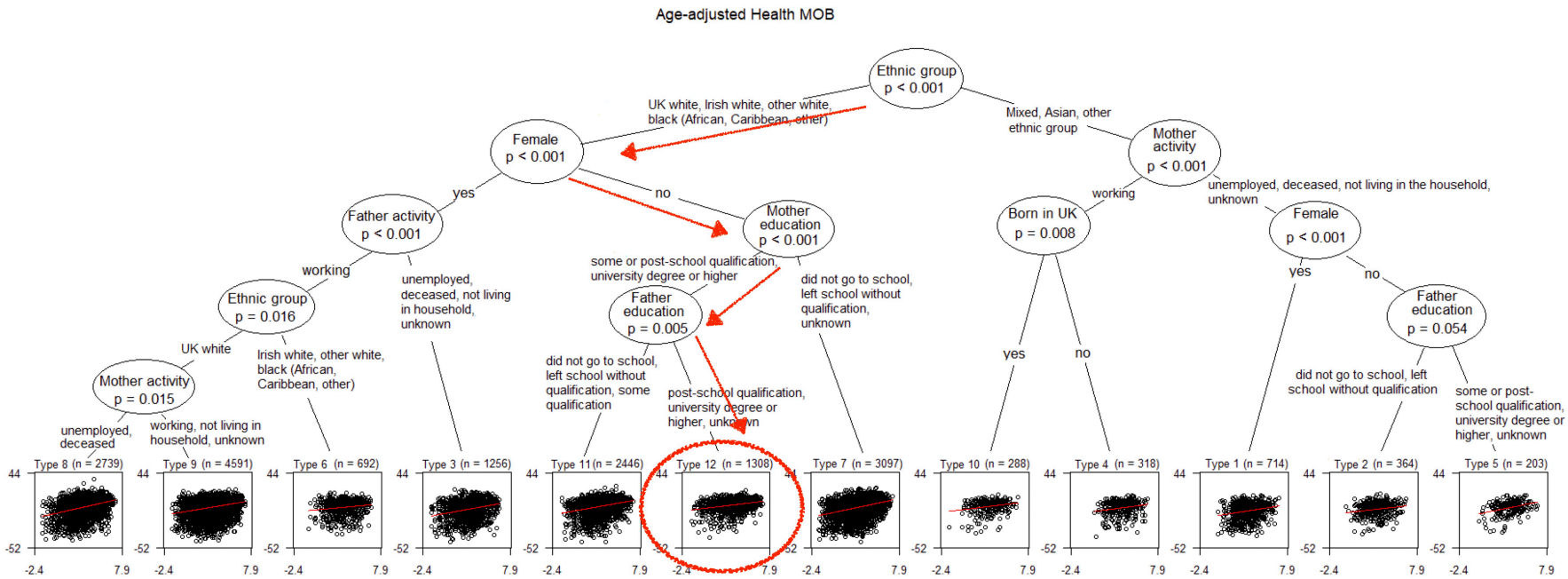
From multidimensional lifestyle to effort



MOB


Age-adjusted Health MOB
Ethnic group
p < 0.001
UK white, Irish white, other white, black (African, Caribbean, other)
Mixed, Asian, other ethnic group
Female
p < 0.001
Mother activity
p < 0.001
yes
no
working
unemployed, deceased, not living in the household, unknown
Father activity
p < 0.001
Mother education
p < 0.001
Born in UK
p = 0.008
Female
p < 0.001
working
unemployed, deceased, not living in household, unknown
some or post-school qualification, university degree or higher
did not go to school, left school without qualification, unknown
yes
no
yes
no
Ethnic group
p = 0.016
Father education
p = 0.005
Father education
p = 0.054
UK white
Irish white, other white, black (African, Caribbean, other)
did not go to school, left school without qualification, some qualification
post-school qualification, university degree or higher, unknown
did not go to school, left school without qualification
some or post-school qualification, university degree or higher, unknown
Mother activity
p = 0.015
unemployed, deceased
working, not living in household, unknown
Type 8 (n = 2739)
Type 9 (n = 4591)
Type 6 (n = 692)
Type 3 (n = 1256)
Type 11 (n = 2446)
Type 12 (n = 1308)
Type 7 (n = 3097)
Type 10 (n = 288)
Type 4 (n = 318)
Type 1 (n = 714)
Type 2 (n = 364)
Type 5 (n = 203)
44
-52
-2.4
7.9

MOB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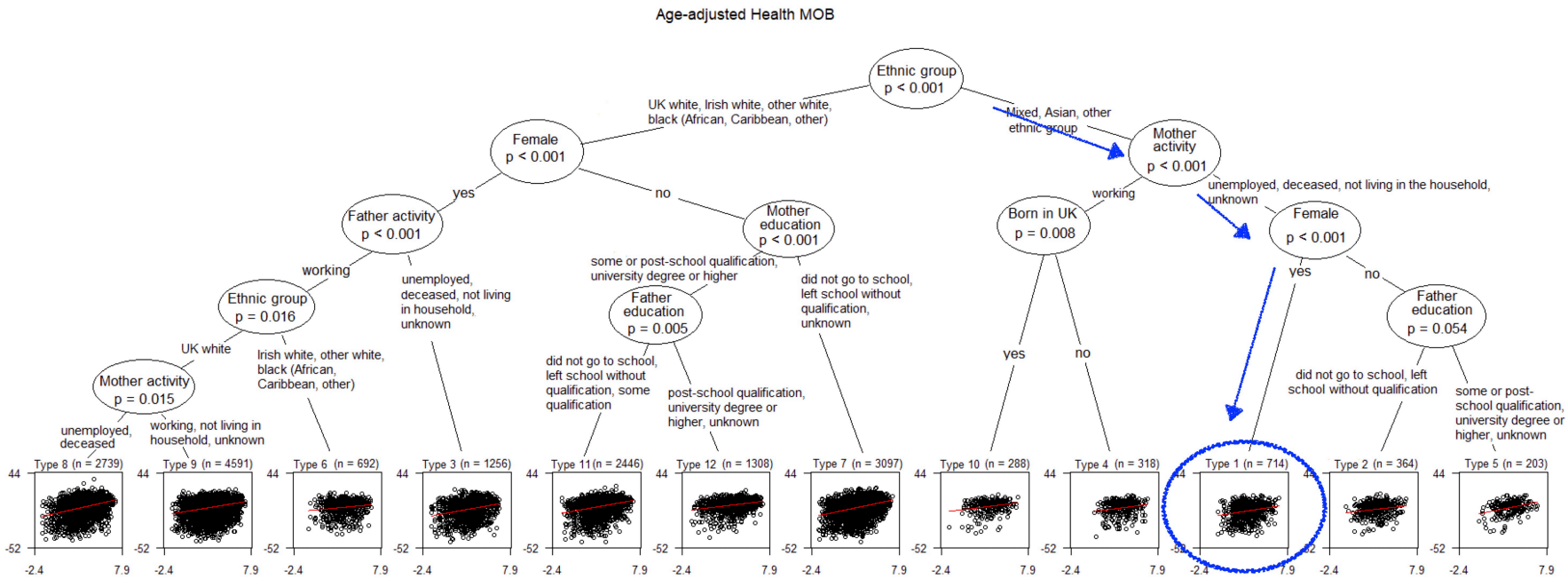
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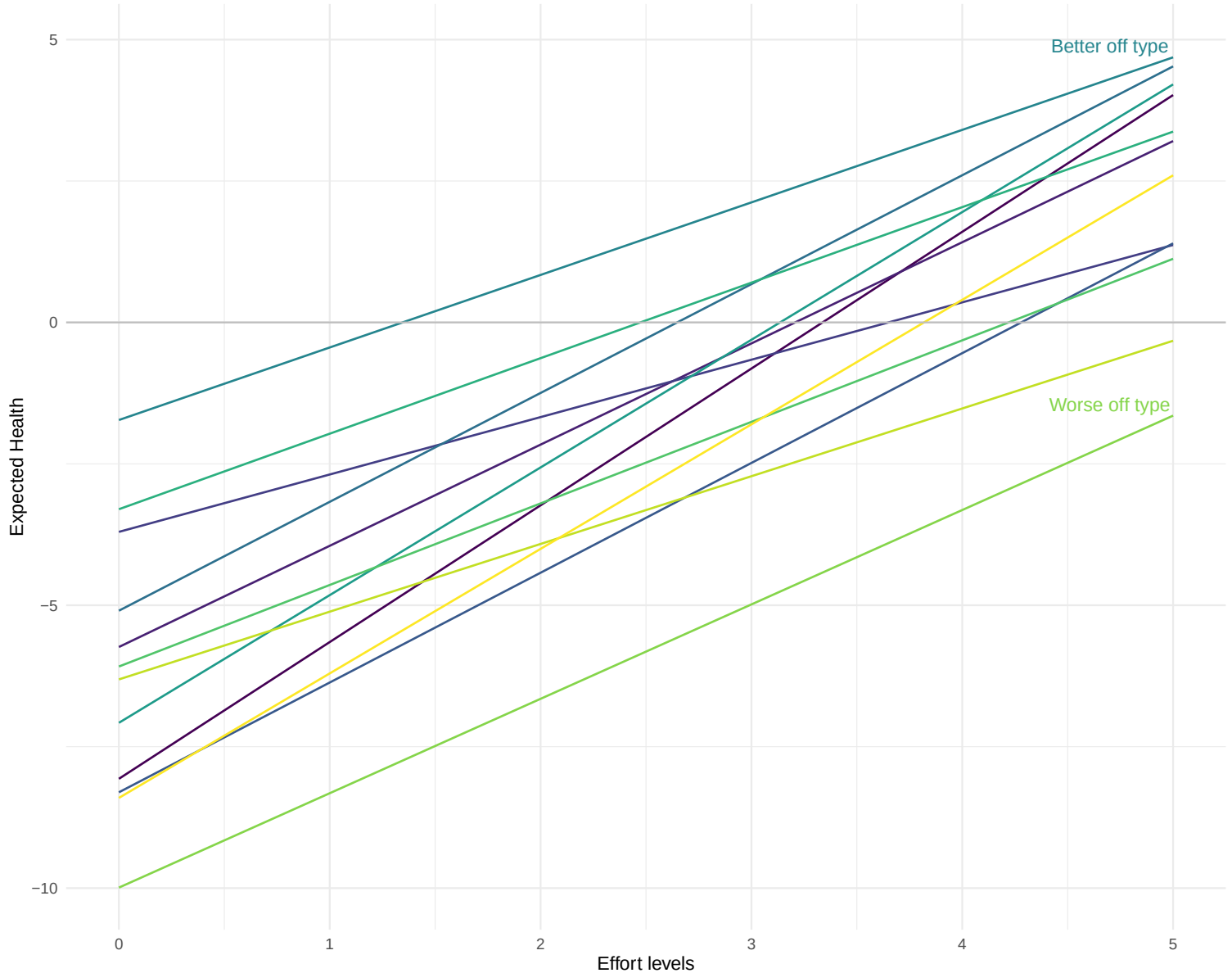
MOB, cnt.

MOB parameters

Type	Av. h	Av. eff	% Pop.	β_0	SE	β_1	SE
1	-4.728	3.153	3.96	-9.991***	(0.991)	1.668***	(0.290)
2	-2.606	3.093	2.02	-6.310***	(1.169)	1.197***	(0.346)
3	-2.400	3.042	6.97	-8.306***	(0.702)	1.940***	(0.204)
4	-0.755	3.695	1.76	-6.082***	(1.634)	1.441***	(0.418)
5	-0.608	3.542	1.12	-8.405***	(1.651)	2.201***	(0.434)
6	-0.063	3.587	3.84	-3.702***	(0.966)	1.014***	(0.249)
7	0.082	3.172	17.19	-7.077***	(0.428)	2.257***	(0.120)
8	0.380	3.494	15.20	-8.067***	(0.534)	2.417***	(0.140)
9	0.487	3.480	25.48	-5.737***	(0.371)	1.788***	(0.097)
10	1.172	3.351	1.59	-3.302***	(1.218)	1.335***	(0.334)
11	1.494	3.424	13.57	-5.095***	(0.459)	1.924***	(0.122)
12	2.871	3.584	7.26	-1.725***	(0.485)	1.282***	(0.123)

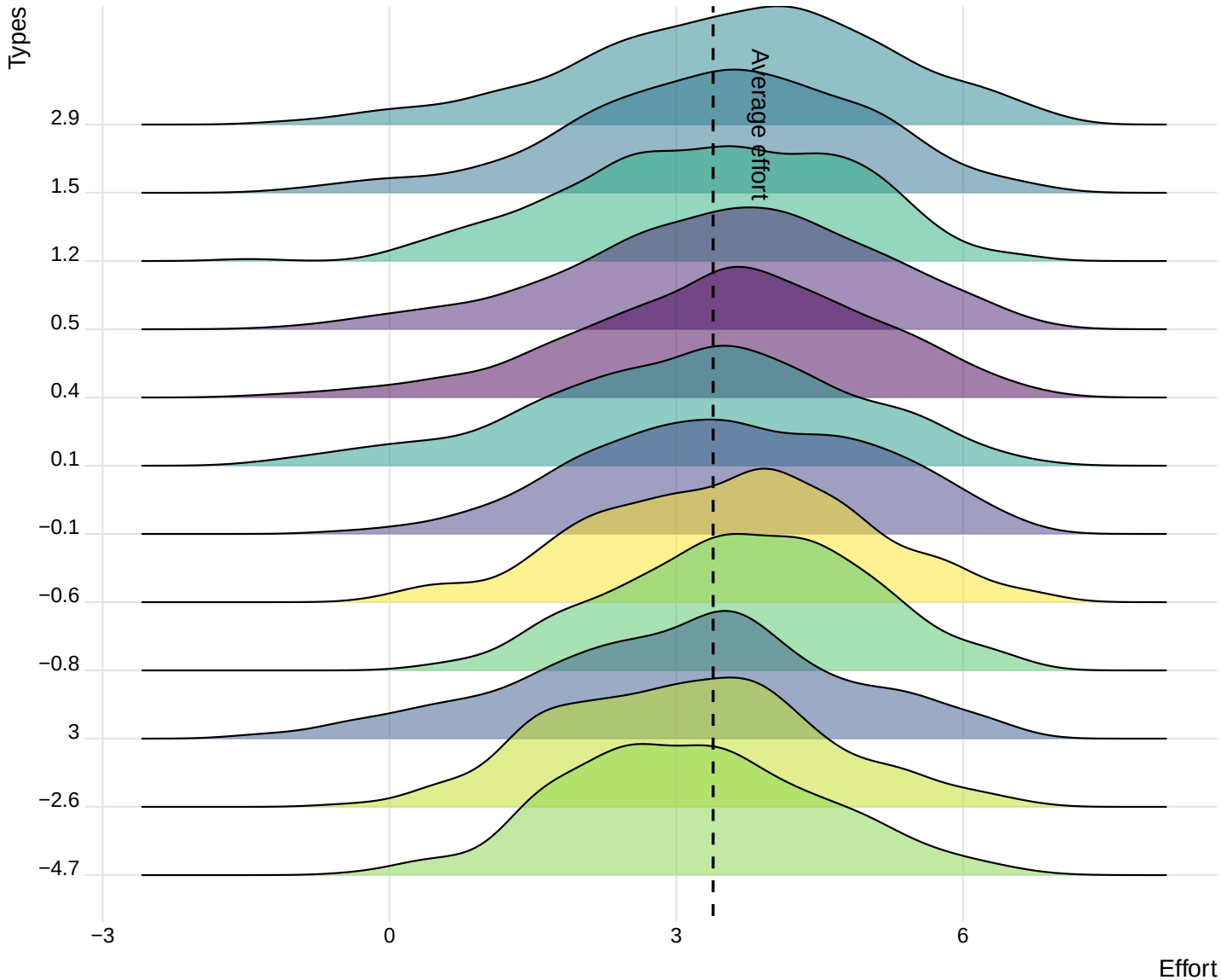
MOB


Better off type
Worse off type
Expected Health
Effort levels
5
0
−5
−10
0
1
2
3
4
5

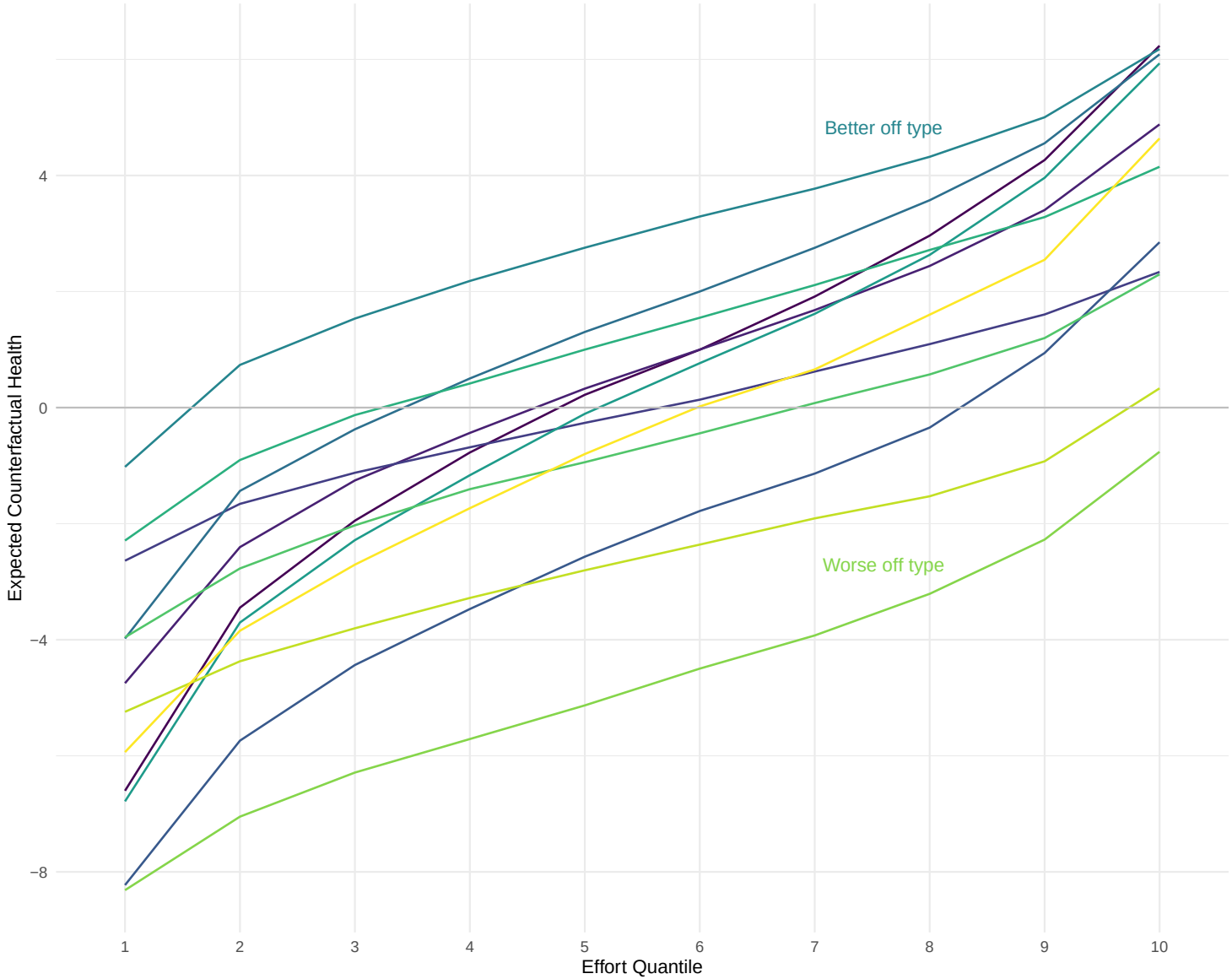
‘Degree of effort’ Vs.‘level of effort’ (Roemer, 1998)

- The morally relevant level of effort is not effort itself;
- individuals in worse-off types may find harder to exert effort;
- ... a secondary effect of circumstances;
- Following Roemer (1998) we define ‘degree of effort’ the quantiles of the type-specific effort distribution.

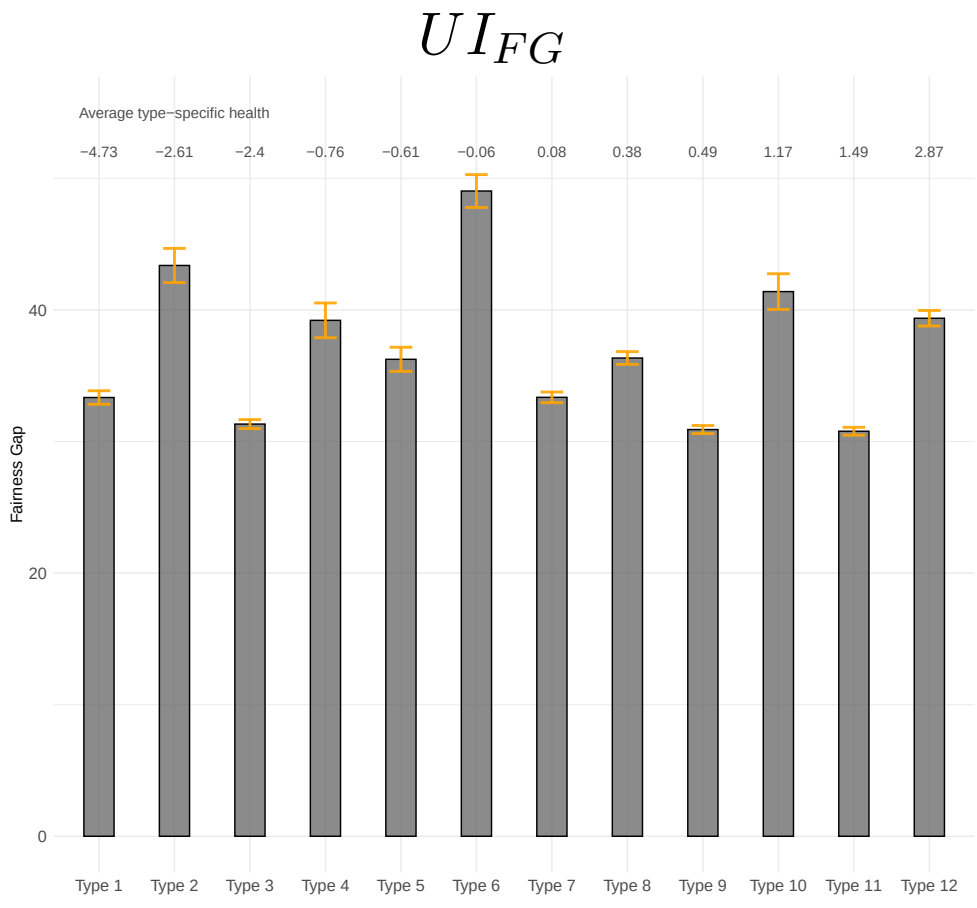
Types effort distributions



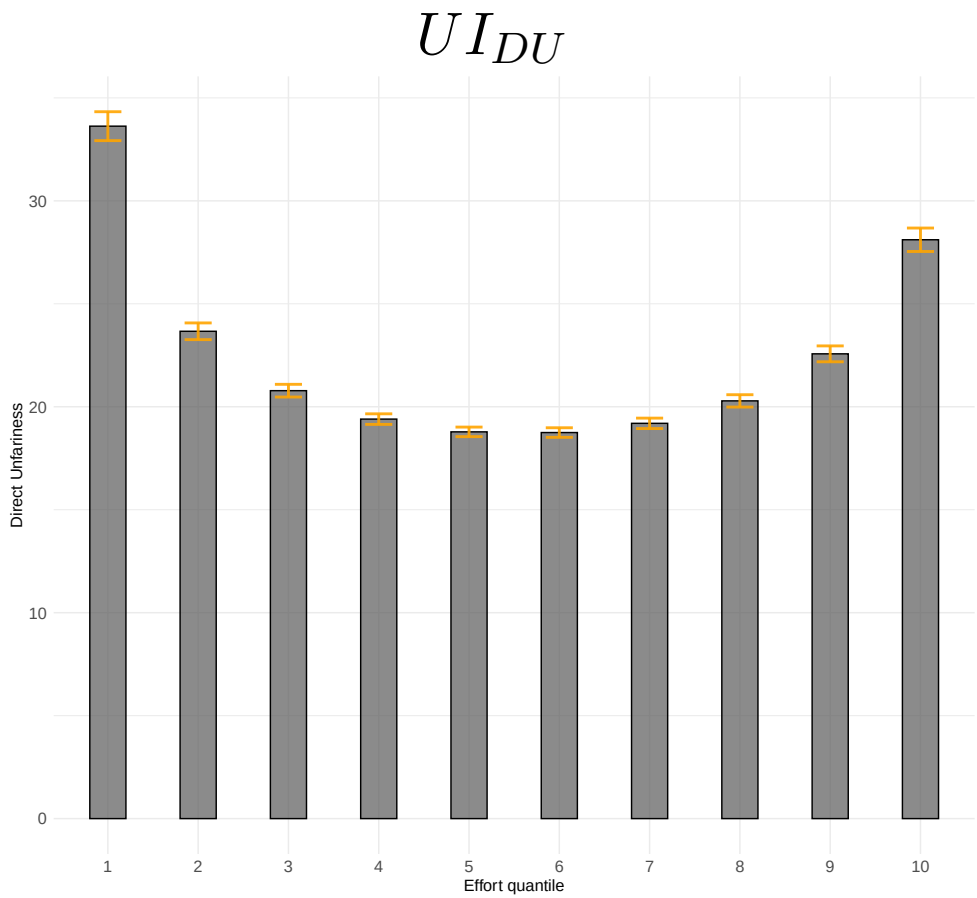
$\tilde{H}$


Better off type
Worse off type
Expected Counterfactual Health
4
0
−4
−8
1
2
3
4
5
6
7
8
9
10
Effort Quantile

UI_{FG}


UI_{FG}
Average type−specific health
−4.73
−2.61
−2.4
−0.76
−0.61
−0.06
0.08
0.38
0.49
1.17
1.49
2.87
Fairness Gap
40
20
0
Type 1
Type 2
Type 3
Type 4
Type 5
Type 6
Type 7
Type 8
Type 9
Type 10
Type 11
Type 12

UI_{DU}


UI_{DU}
Direct Unfariness
0
10
20
30
1
2
3
4
5
6
7
8
9
10
Effort quantile

Conclusions

- MOB a promising tool to measure unfair inequalities;
- extremely data-demanding;
- explained variability is low (8%) but up to 50% is unfair;
- (apparently harmless) normative choices implies large difference in UI;
- trade-off: theoretical soundness vs. interpretability