Uncertainty in MRIO-based GHG footprints

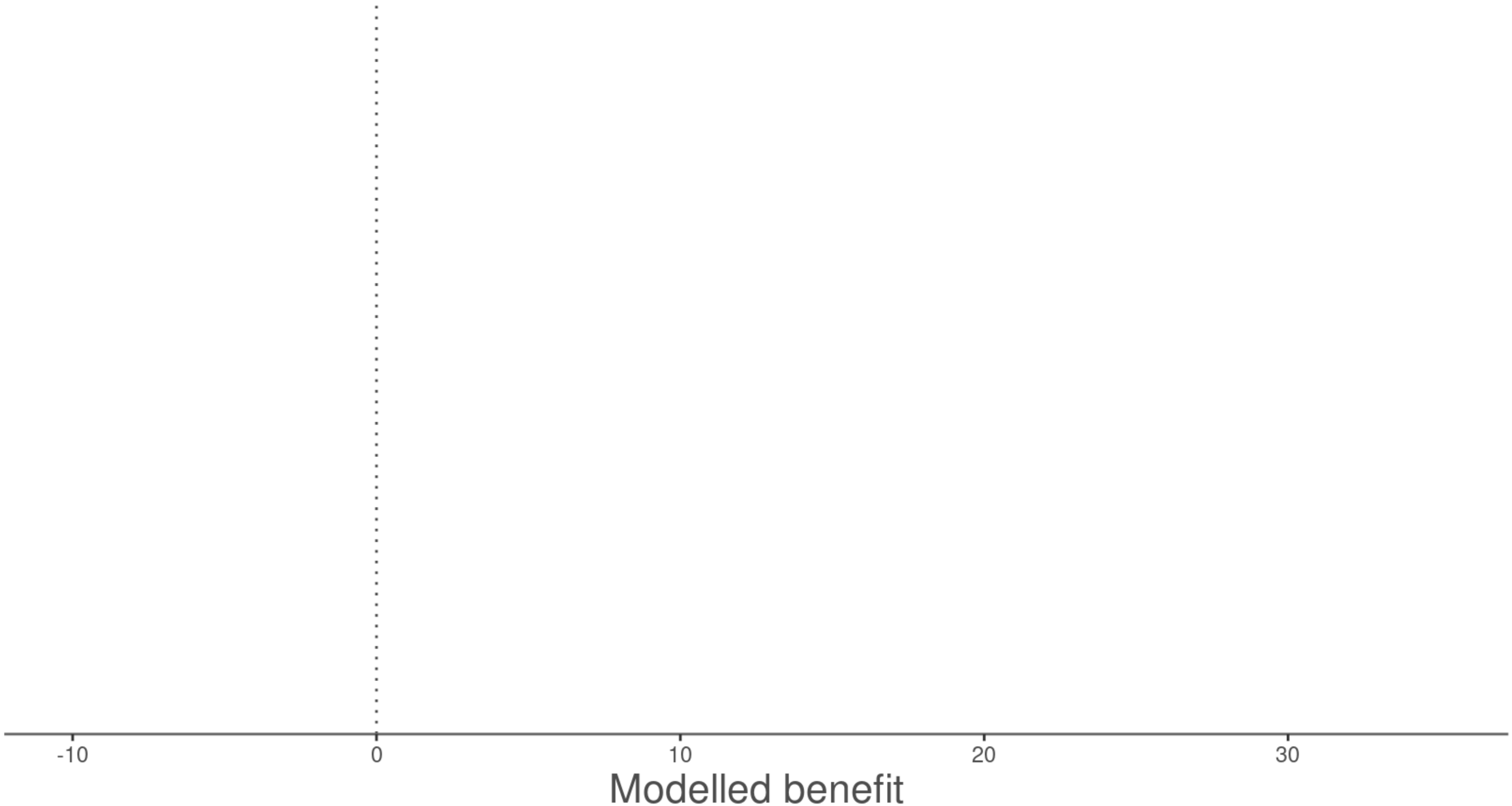
15. Input-Output-Workshop Osnabrück

Simon Schulte*, Arthur Jakobs, Stefan Pauliuk

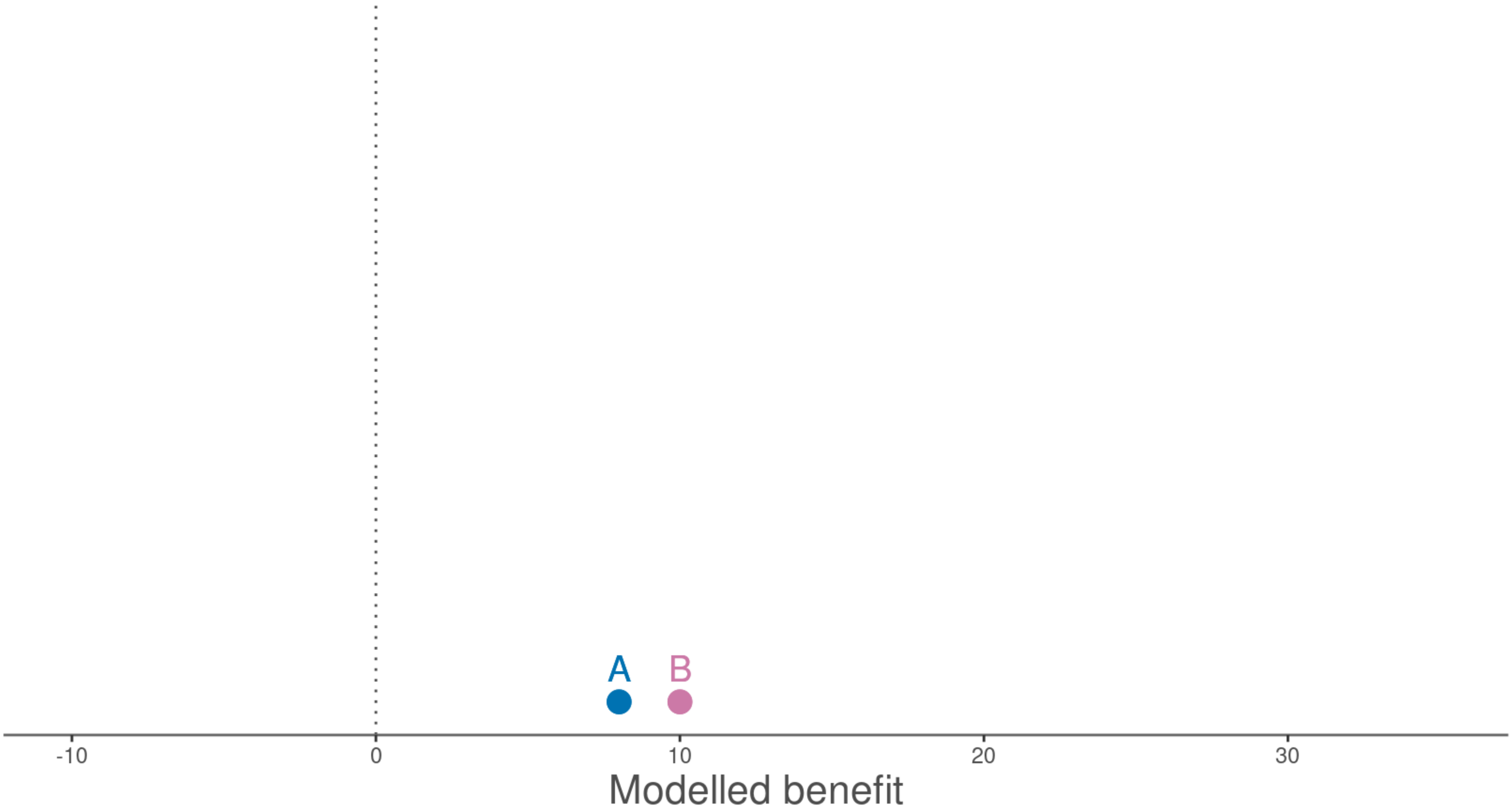
2024-03-01

universität freiburg

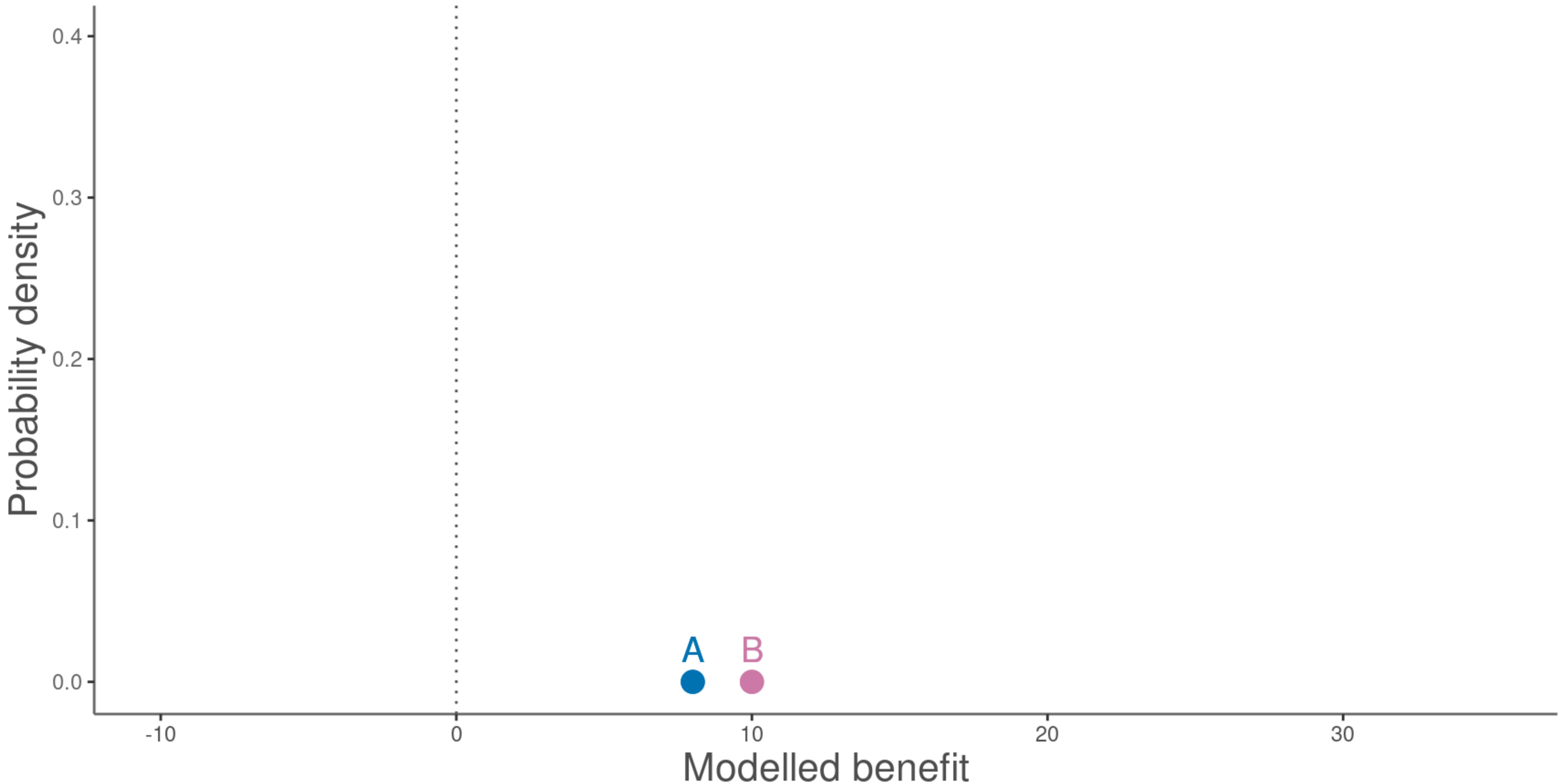
universität freiburg


-10
0
10
20
30
Modelled benefit

Which option would you choose as a decision-maker?

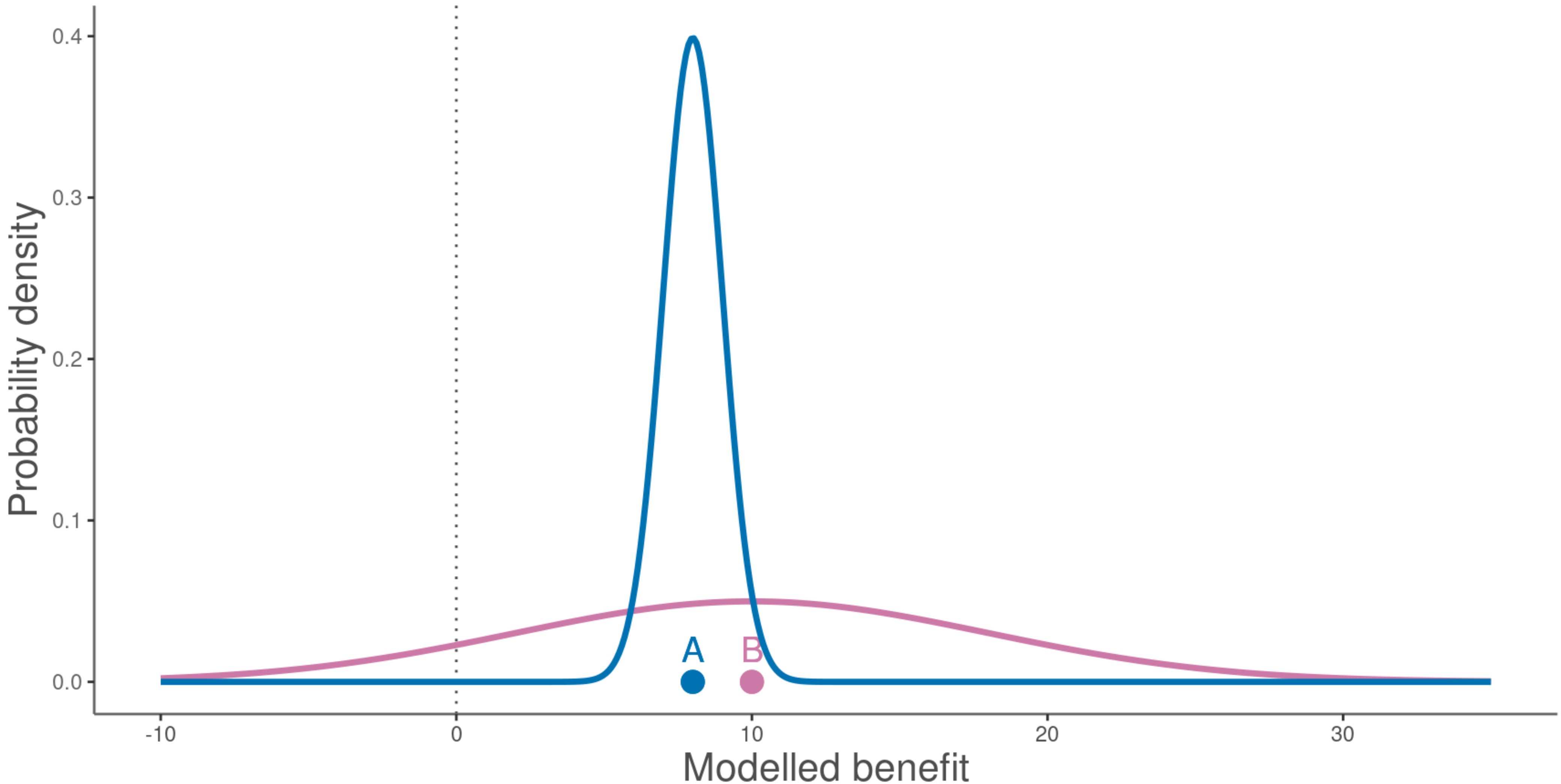


Which option would you choose as a decision-maker?



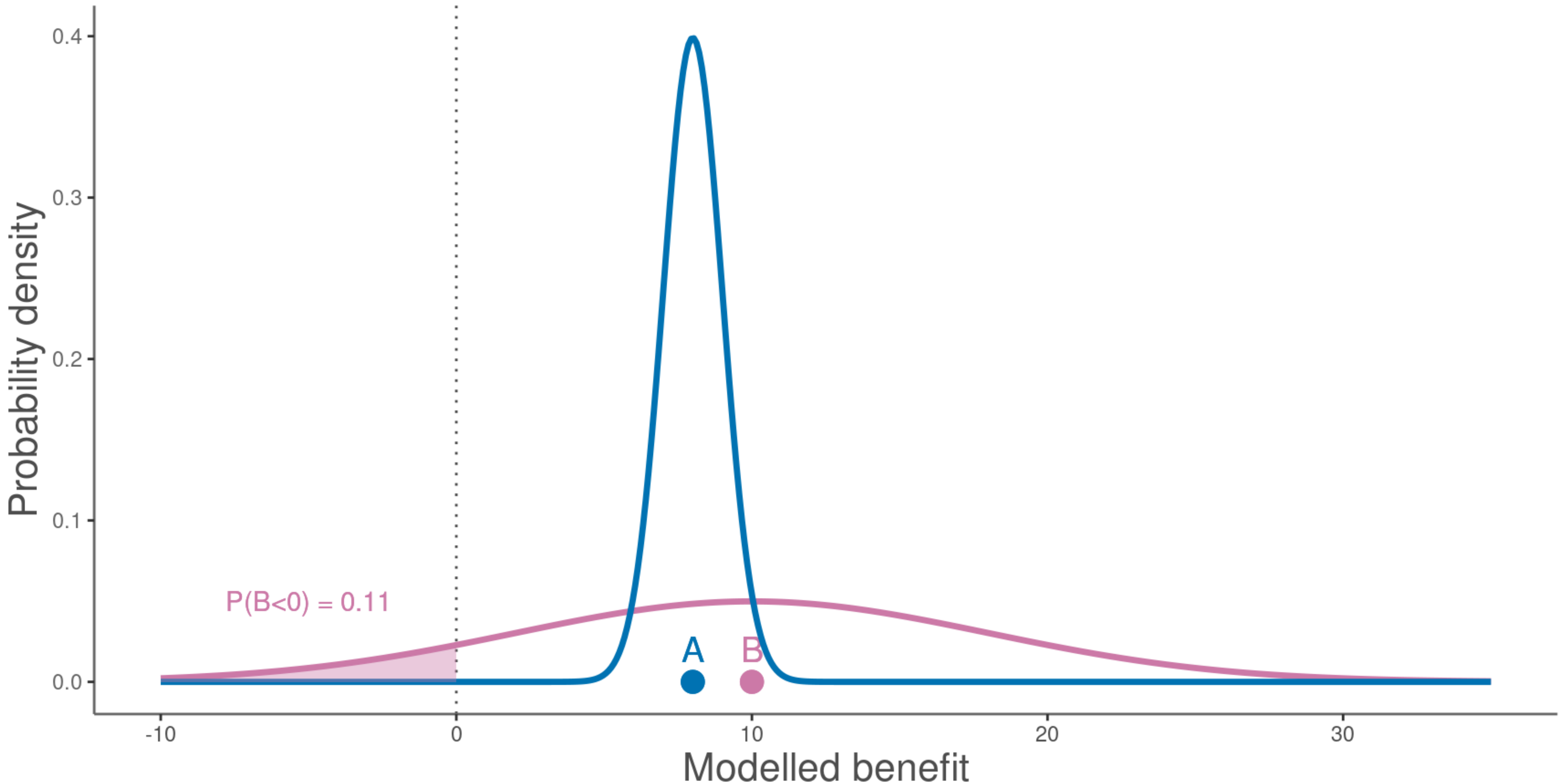
universität freiburg

And now?

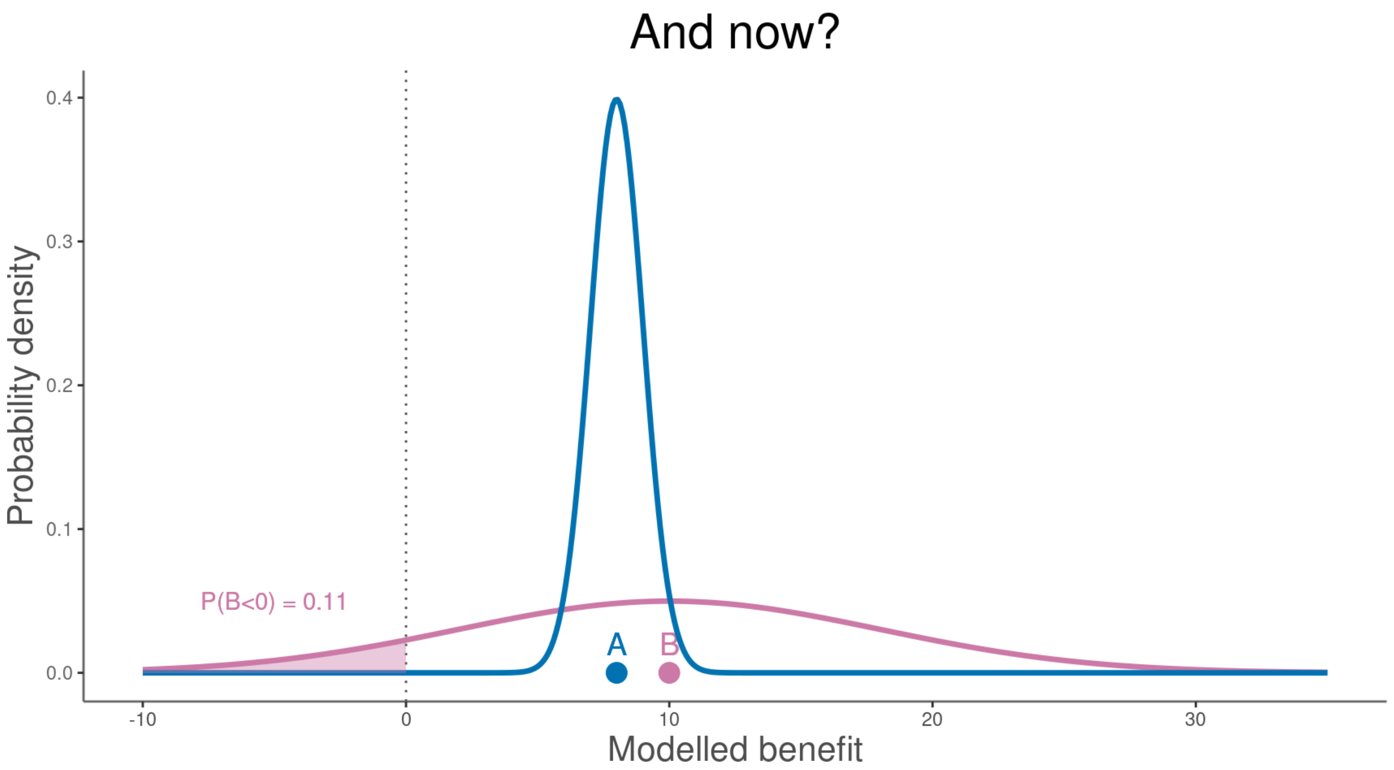


universität freiburg

And now?



Probability density
0.4
0.3
0.2
0.1
0.0
P(B<0) = 0.11
A
B
-10
0
10
20
30
Modelled benefit



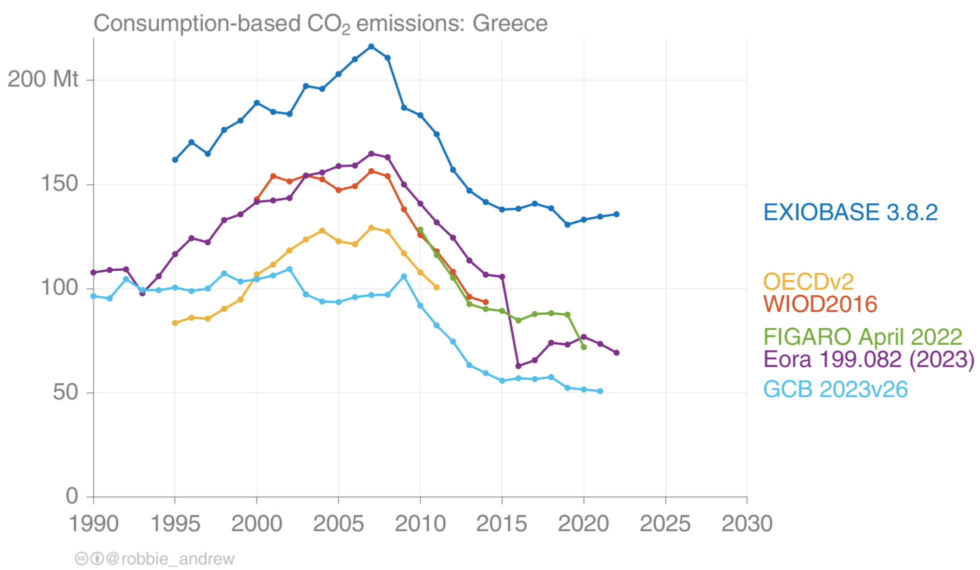
Model uncertainty matters…

- … for robust decision-making
- … to guide GMRIO compilers to “uncertainty hot-spots” to allocate resources more efficiently

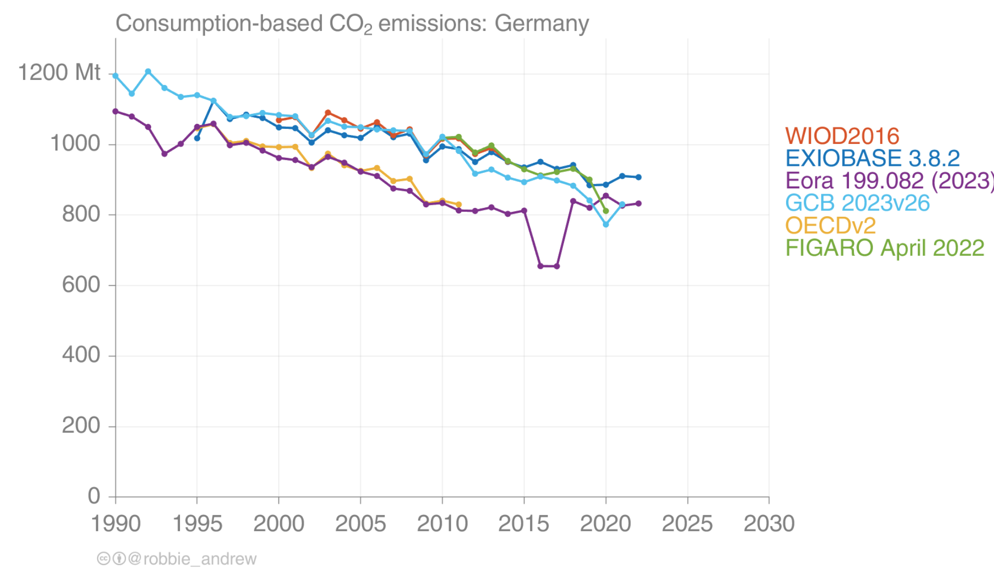
universität freiburg

Uncertainty in EE-MRIO: Current state

- database comparisons: Satellite accounts are largest source of discrepancy



https://robbieandrew.github.io/consumption/index.html



https://robbieandrew.github.io/consumption/index.html

Uncertainty in EE-MRIO: Current state

- database comparisons: Satellite accounts are largest source of discrepancy
- mostly points estimates, and, if at all, *qualitative* considerations of uncertainty
- few studies provide *quantitative* estimation of parametric uncertainties [1–8]
- two GMRIO databases that publish uncertainty estimates alongside each data entry (*except for GHG extensions*): Eora [9] & GLORIA [10]
- all studies use Monte-Carlo (MC) simulations to propagate uncertainty from model input parameters to model outputs

Aim and scope of our study

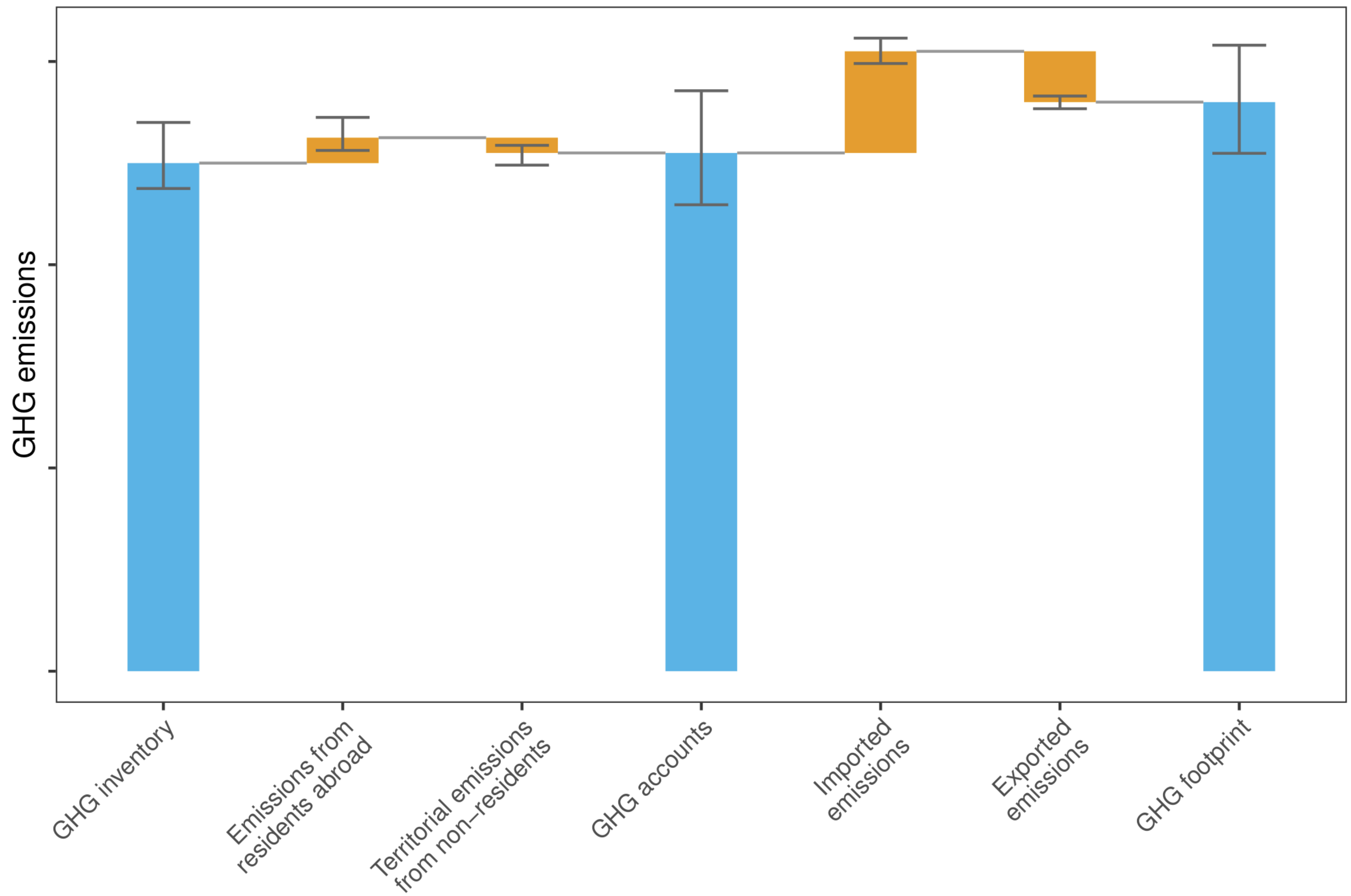
- estimate the parametric uncertainty of the GHG satellite accounts
- estimate how the uncertainty propagates to GHG footprints
- overcome two shortcomings from previous approaches:
  - #1: Uncertainty of the raw input data based on simplistic assumptions
  - #2: Correlations between variables obtained by disaggregating a common input data point are ignored

- Scope:
  - Year 2015
  - GHGs CO_2, CH_4, N_2O
  - EXIOBASE country/sector resolution

Compiling GHG accounts

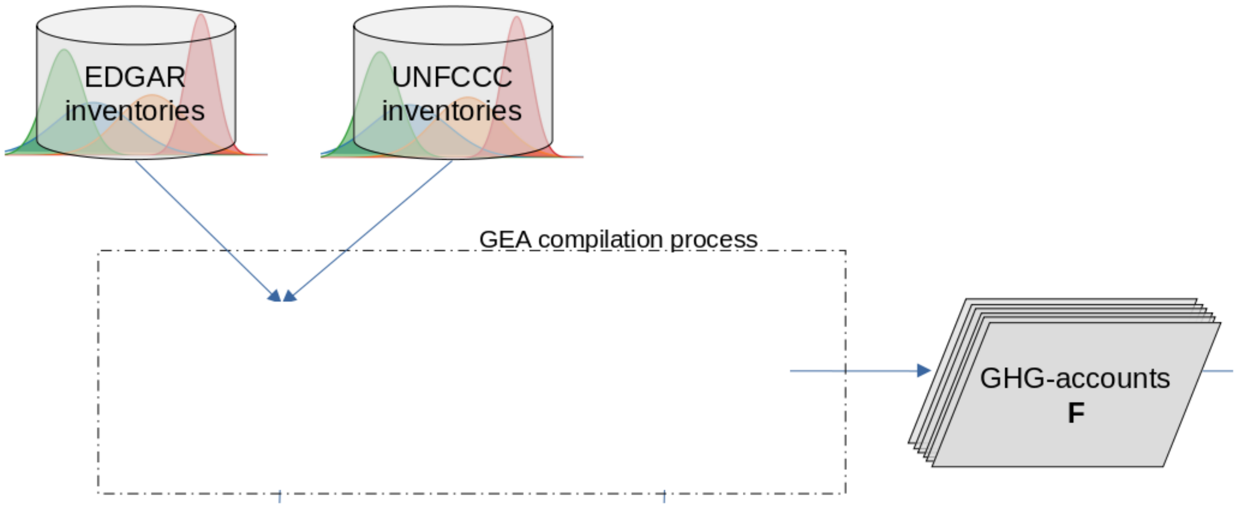
Statistical concept

National GHG emissions from three perspectives



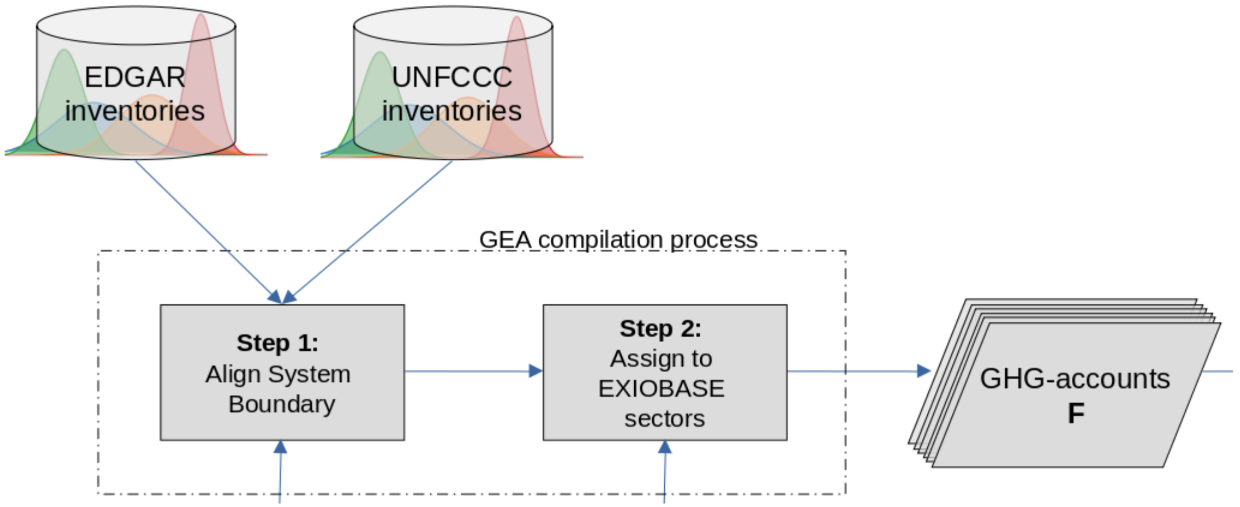
universität freiburg

Our workflow

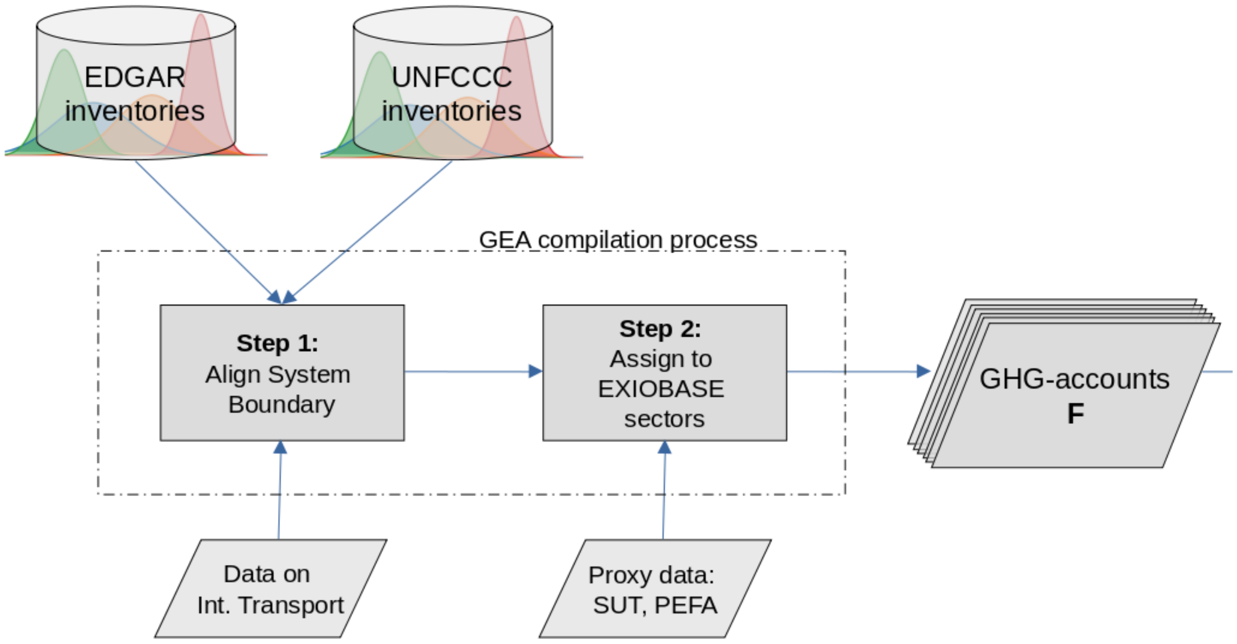


universität freiburg

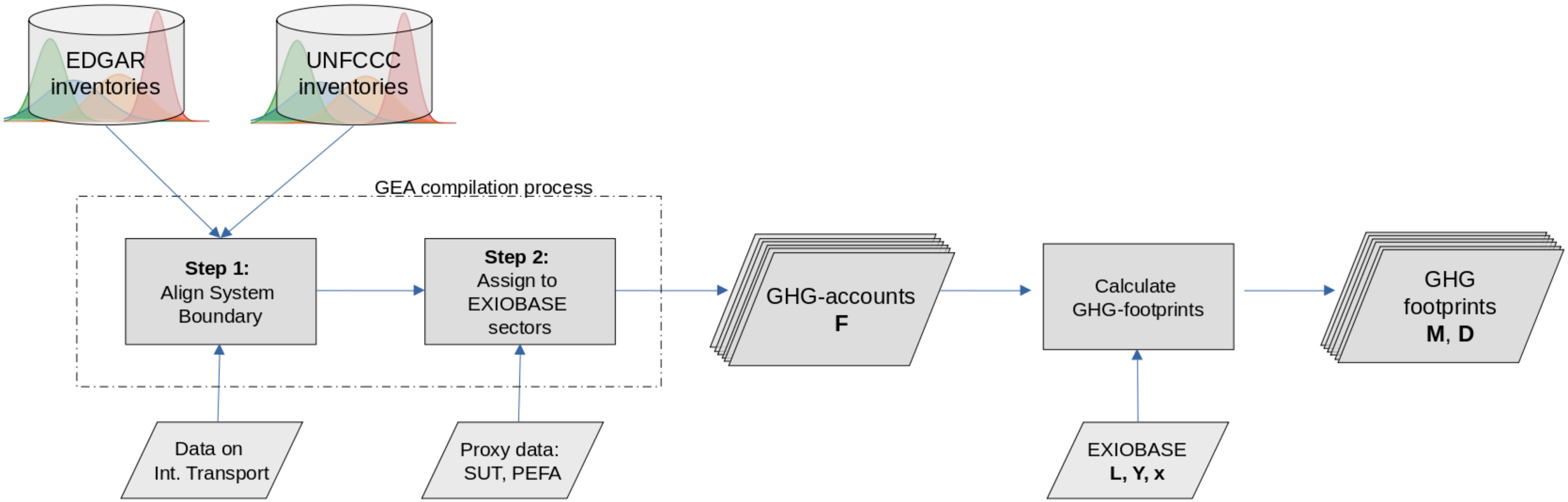
Our workflow



Our workflow



Our workflow



Overcoming shortcomings of previous approaches

#1: Uncertainty of the raw input data based on simplistic assumptions

Two common approaches

Heuristics:

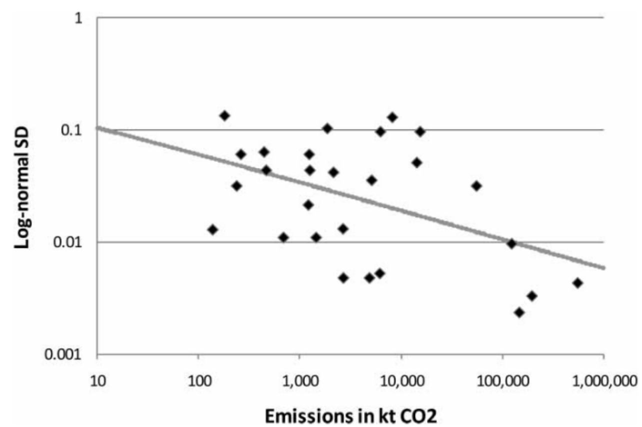
TABLE 3. Assumptions on uncertainties (%) in technical coefficients (columns) for two groups of sectors in the Monte Carlo analysis.

	Group A	Group B
Domestic inputs from A	5	10
Domestic inputs from B	10	20
Imports from A	10	20
Imports from B	20	40

[2]

Statistical model:

FIGURE 2. Standard deviations for UK CO_2 emissions estimates (adapted from Table A 7.6.1 in Jackson et al. 2009a, p. 495).



Note: $r_x = 0.486x^{-0.261}$, $R^2 = 0.212$.

[1]

Our approach

Climate Change: National Inventory Report, Germany – 2017

Table 546: Table 6.1 of the IPCC Good Practice Guidance – details

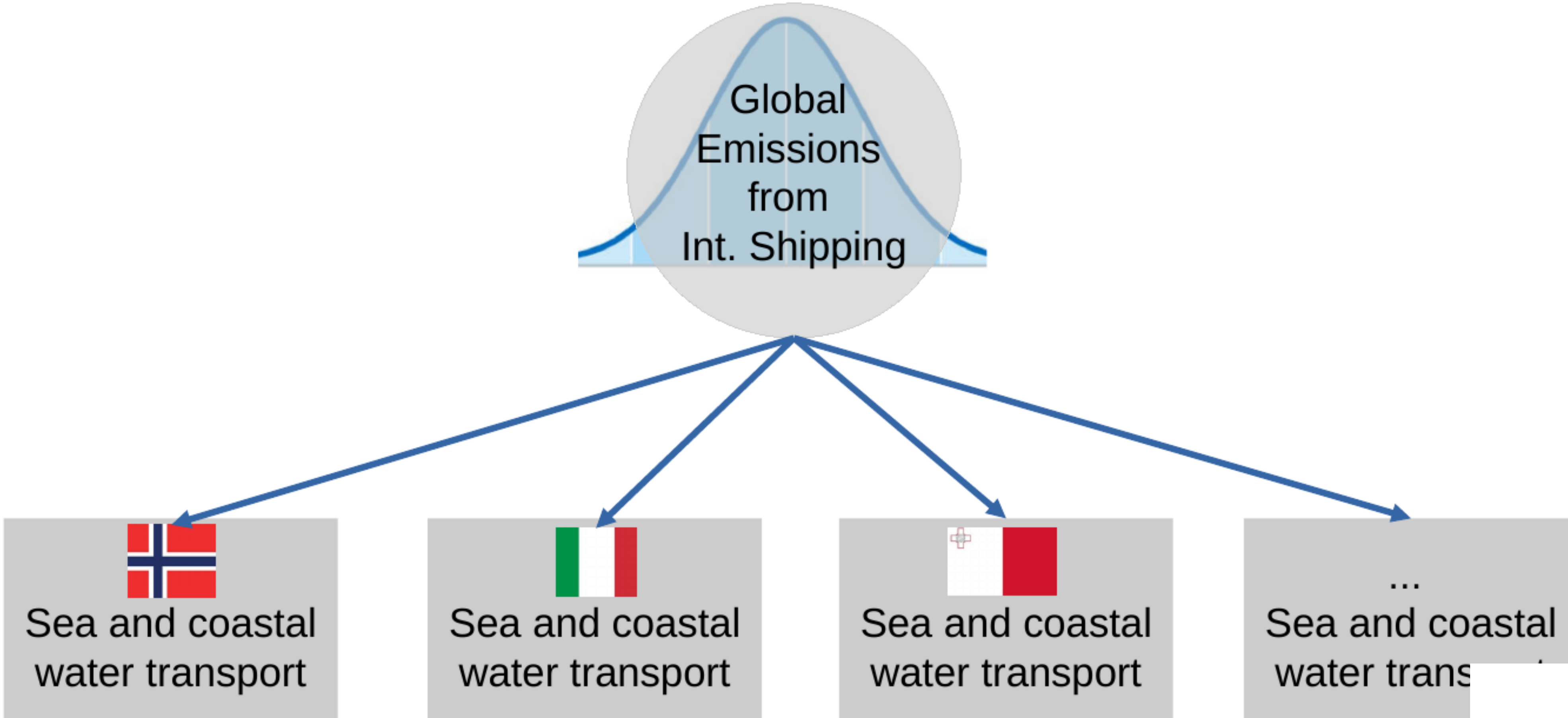
A	B	C	D	E	F	G	H	I	J	K	L	M
IPCC category	Gas	Base year emissions or removals	Year *x* emissions or removals	Activity data uncertainty	Emission factor / estimation parameter uncertainty	Combined uncertainty	Contribution to Variance by Category in Year x	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national emissions introduced by emission factor / estimation parameter uncertainty	Uncertainty in trend in national emissions introduced by activity data uncertainty	Uncertainty introduced into the trend in total national emissions
		Input data	Input data	Input data Note A	Input data Note A	$\sqrt{E^2+F^2}$	$\frac{(G*D)^2}{(\sum D)^2}$	Note B	$\left\|\frac{D}{\sum C}\right\|$	$I*F$ Note C	$J*E*\sqrt{2}$ Note D	K^2+L^2
		kt CO_2 equivalent	kt CO_2 equivalent	%	%	%		%	%	%	%	%
1 A 1 a	Methane	244770.58	2559966.75	0.0000	71.0906	71.0906	3.26E-02	1.90E-03	2.06E-03	2.07E-01	0.00E+00	4.27E-02
1 A 1 a	Carbon dioxide	304600122.51	301705650.80	0.0000	4.6445	4.6445	1.93E+00	4.43E-02	2.42E-01	1.59E+00	0.00E+00	2.53E+00
1 A 1 a	Nitrous oxide	2109962.22	2423300.96	0.0000	20.7043	20.7043	2.48E-03	5.75E-04	1.95E-03	5.70E-02	0.00E+00	3.25E-03
1 A 1 b	Carbon dioxide	19131150.13	18154030.06	0.0000	5.7356	5.7356	1.07E-02	2.15E-03	1.46E-02	1.18E-01	0.00E+00	1.40E-02
1 A 1 b	Methane	14926.14	13704.45	0.0000	17.1506	17.1506	5.44E-08	1.31E-06	1.10E-05	2.67E-04	0.00E+00	7.2E-08
1 A 1 b	Nitrous oxide	62566.66	55832.25	0.0000	30.2204	30.2204	2.80E-06	4.19E-06	4.48E-05	1.92E-03	0.00E+00	3.67E-06
1 A 1 c	Methane	135624.34	171852.71	0.0000	137.7831	137.7831	5.52E-04	4.99E-05	1.38E-04	2.69E-02	0.00E+00	7.23E-04
1 A 1 c	Nitrous oxide	357751.55	154231.64	0.0000	21.9779	21.9779	1.13E-05	1.09E-04	1.24E-04	3.85E-03	0.00E+00	1.48E-05
1 A 1 c	Carbon dioxide	40220524.02	10157932.32	0.0000	5.5004	5.5004	3.08E-03	1.80E-02	8.16E-03	6.34E-02	0.00E+00	4.02E-03
1 A 2 a	Methane	61215.46	68610.95	0.0000	27.3973	27.3973	3.48E-06	1.53E-05	5.51E-05	2.13E-03	0.00E+00	4.56E-06
1 A 2 a	Nitrous oxide	118100.49	118516.09	0.0000	37.0079	37.0079	1.90E-05	1.85E-05	9.52E-05	4.98E-03	0.00E+00	2.48E-05
1 A 2 a	Carbon dioxide	33097558.64	38576031.16	0.0000	6.1025	6.1025	5.46E-02	9.47E-03	3.10E-02	2.67E-01	0.00E+00	7.15E-02
1 A 2 b	Carbon dioxide	2051868.53	1513285.75	0.0000	11.3486	11.3486	2.91E-04	1.18E-04	1.22E-03	1.95E-02	0.00E+00	3.80E-04
1 A 2 b	Methane	1730.36	1693.81	0.0000	71.4351	71.4351	1.44E-08	2.36E-07	1.36E-06	1.37E-04	0.00E+00	1.89E-08
1 A 2 b	Nitrous oxide	13862.87	7679.60	0.0000	67.9640	67.9640	2.68E-07	2.84E-06	6.17E-06	5.93E-04	0.00E+00	3.51E-07
1 A 2 d	Carbon dioxide	6869.00	6074.31	0.0000	5.6766	5.6766	1.17E-09	4.16E-07	4.88E-06	3.92E-05	0.00E+00	1.53E-09
1 A 2 d	Methane	1099.83	2891.88	0.0000	44.5671	44.5671	1.64E-08	1.61E-06	2.32E-06	1.46E-04	0.00E+00	2.14E-08
1 A 2 d	Nitrous oxide	4719.59	12409.61	0.0000	53.4099	53.4099	4.33E-07	6.90E-06	9.96E-06	7.53E-04	0.00E+00	5.66E-07

UNFCCC National Inventory Reports (only in .pdf format 😭)

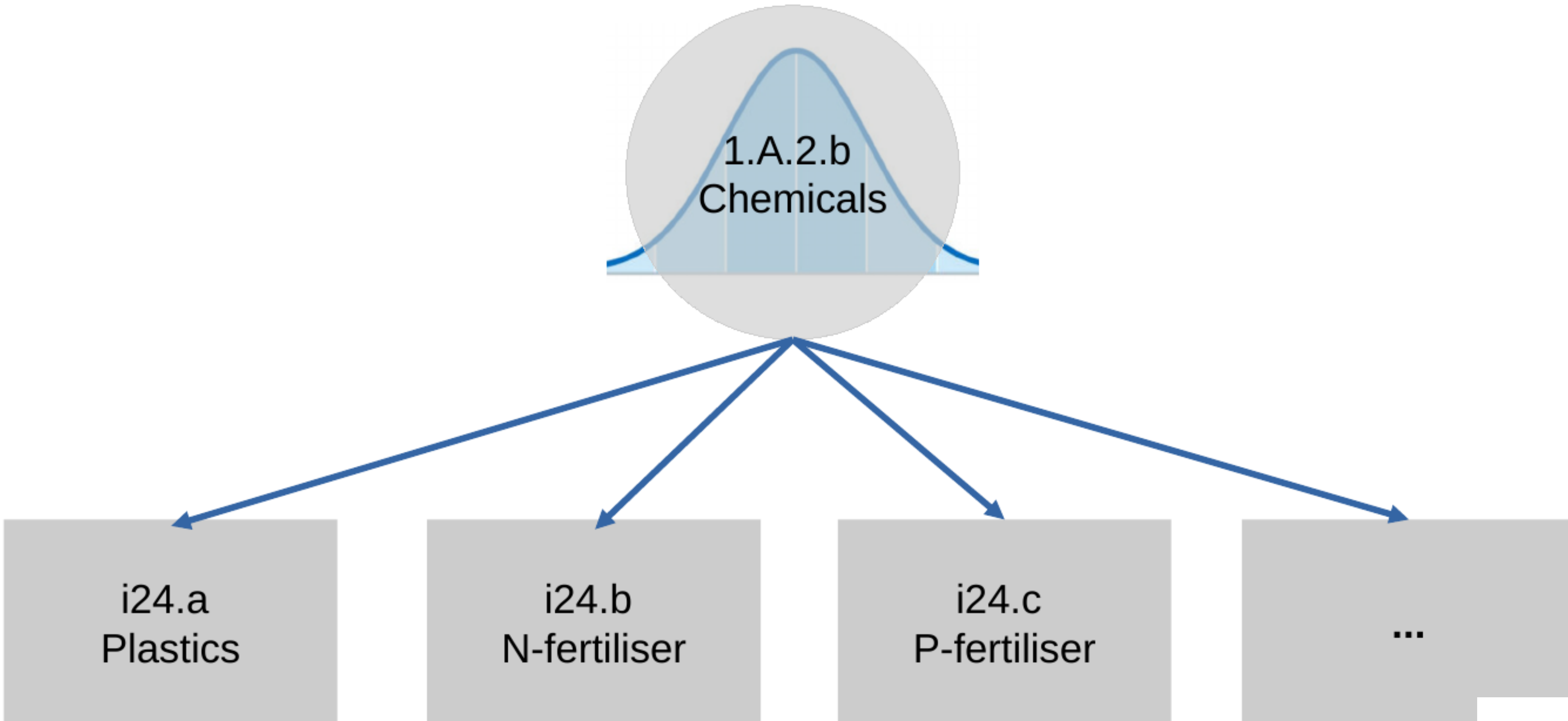
But now, as .csv on Zenodo: https://zenodo.org/records/10037714 😄

#2: A disregard of correlations between variables obtained by disaggregating a common input data point

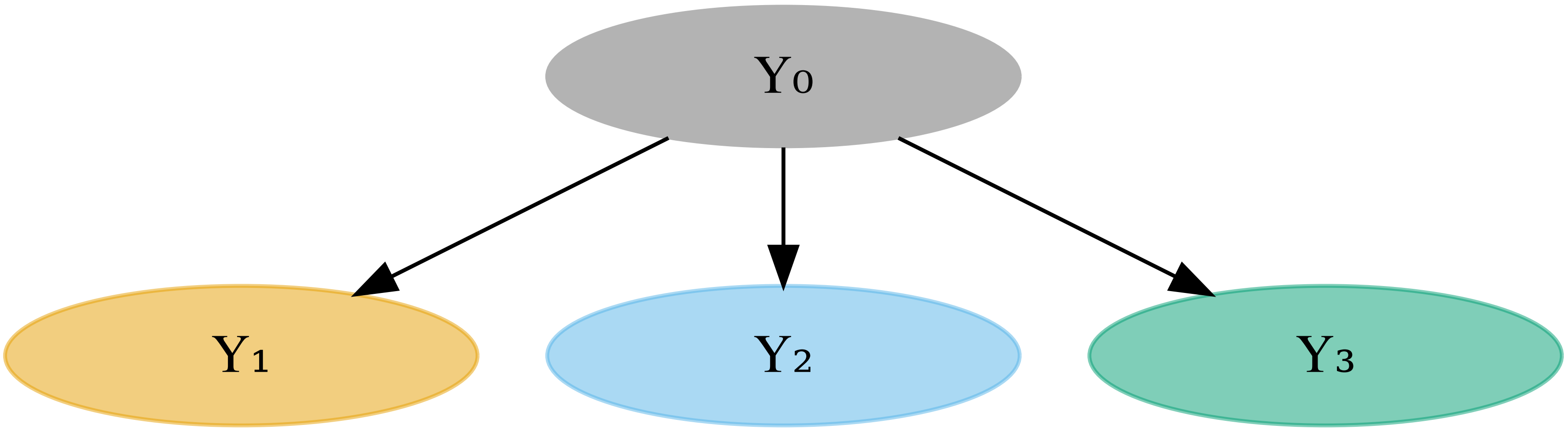
Data disaggregation: Residence adjustment



Data disaggregation: Assign to MRIO sectors

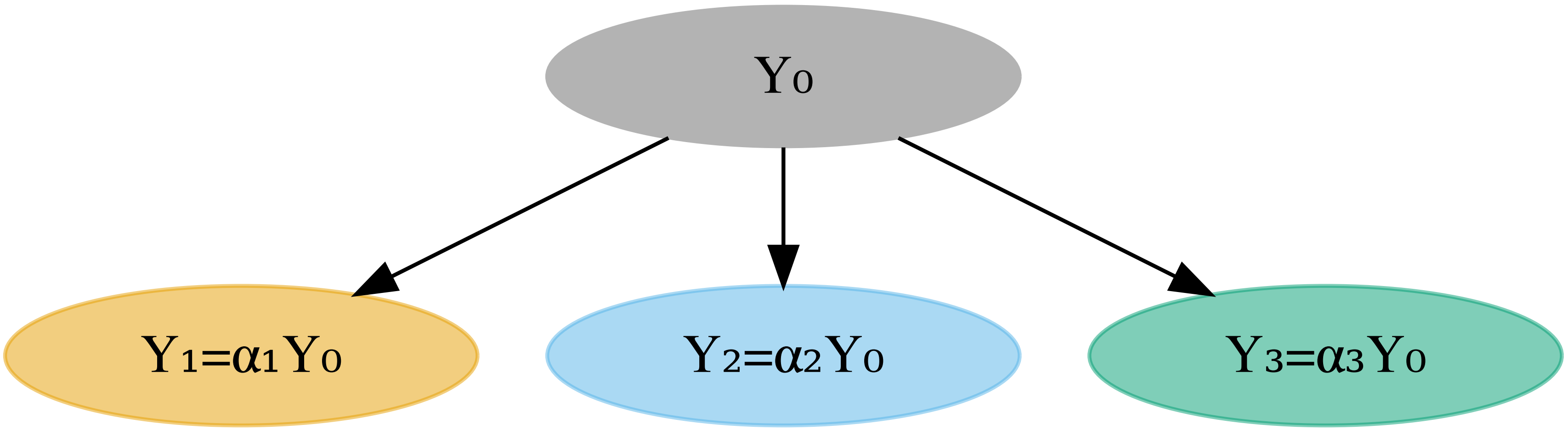


Uncertainty propagation involving data disaggregation



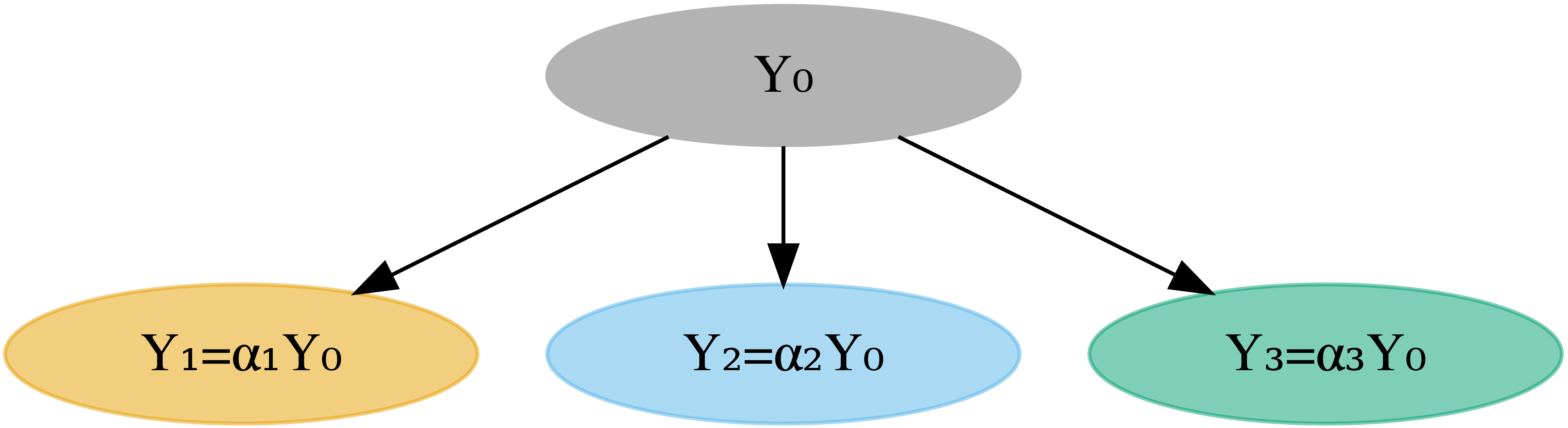
where $\sum Y_i = Y_0$.

Uncertainty propagation involving data disaggregation



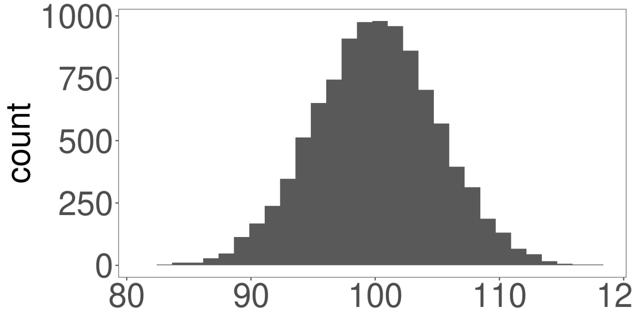
where $\sum \alpha_i = 1.$

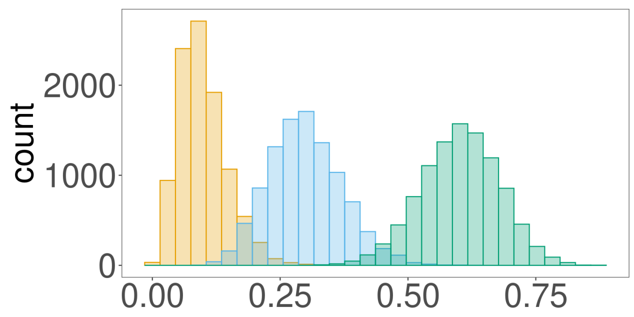
Constraints & Information

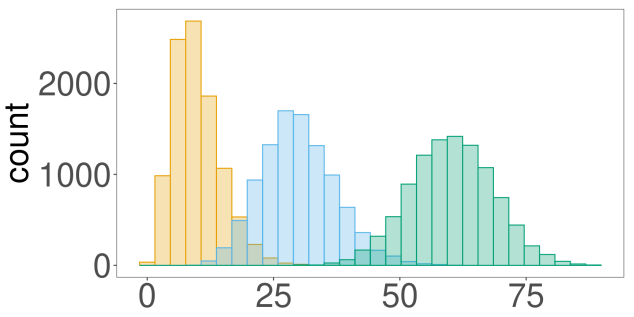


1. **Mean** μ and **Standard Deviation** σ of aggregate data (UNFCCC/EDGAR)
2. **Mean** sector shares for disaggregate data $\boldsymbol{\alpha}$ (proxy data: SUT/PEFA/…)
3. sum-to-one constraint: $\sum \alpha_i = 1$
4. no negative emissions

Sampling procedure





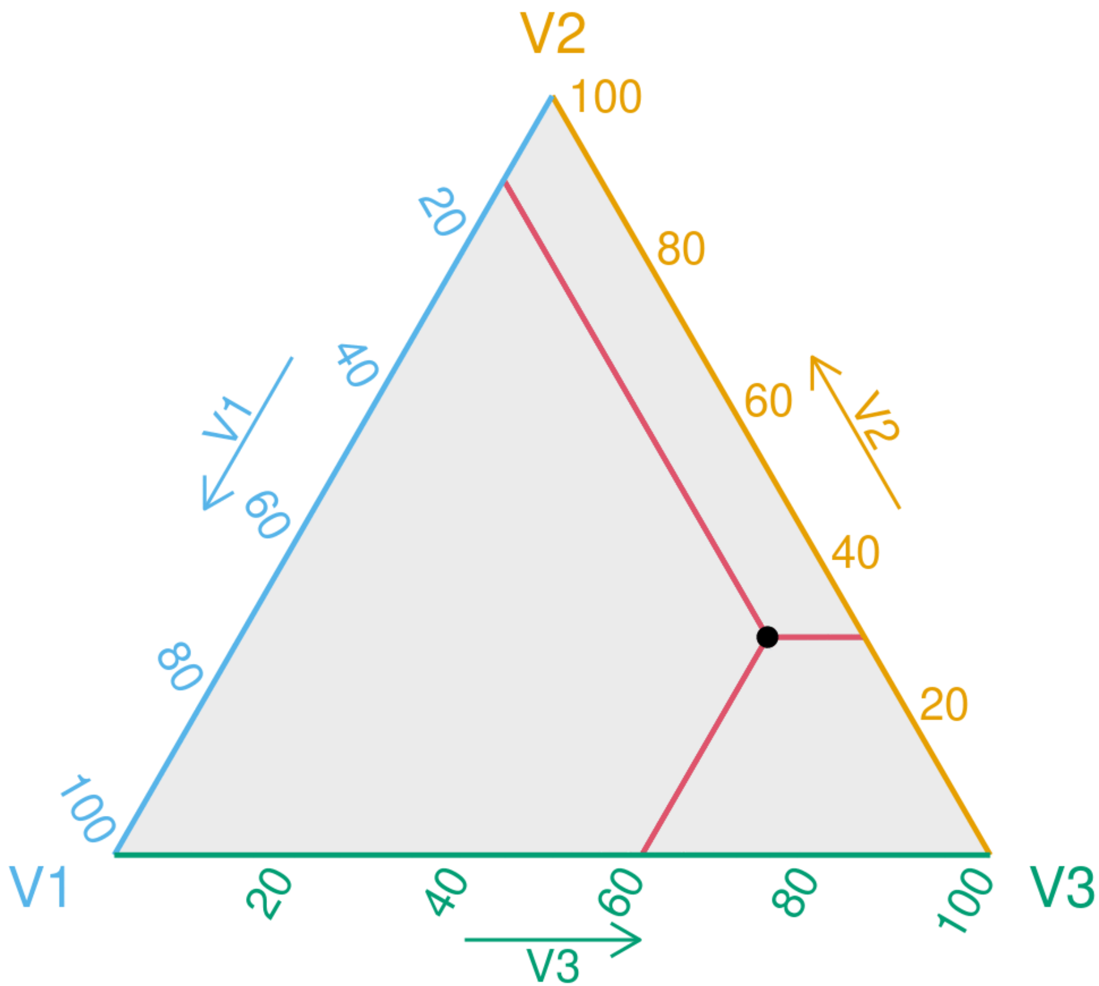


Step 1: Sample aggregate data from truncated normal distribution: $y_0 \sim tN(\mu, \sigma, a = 0)$

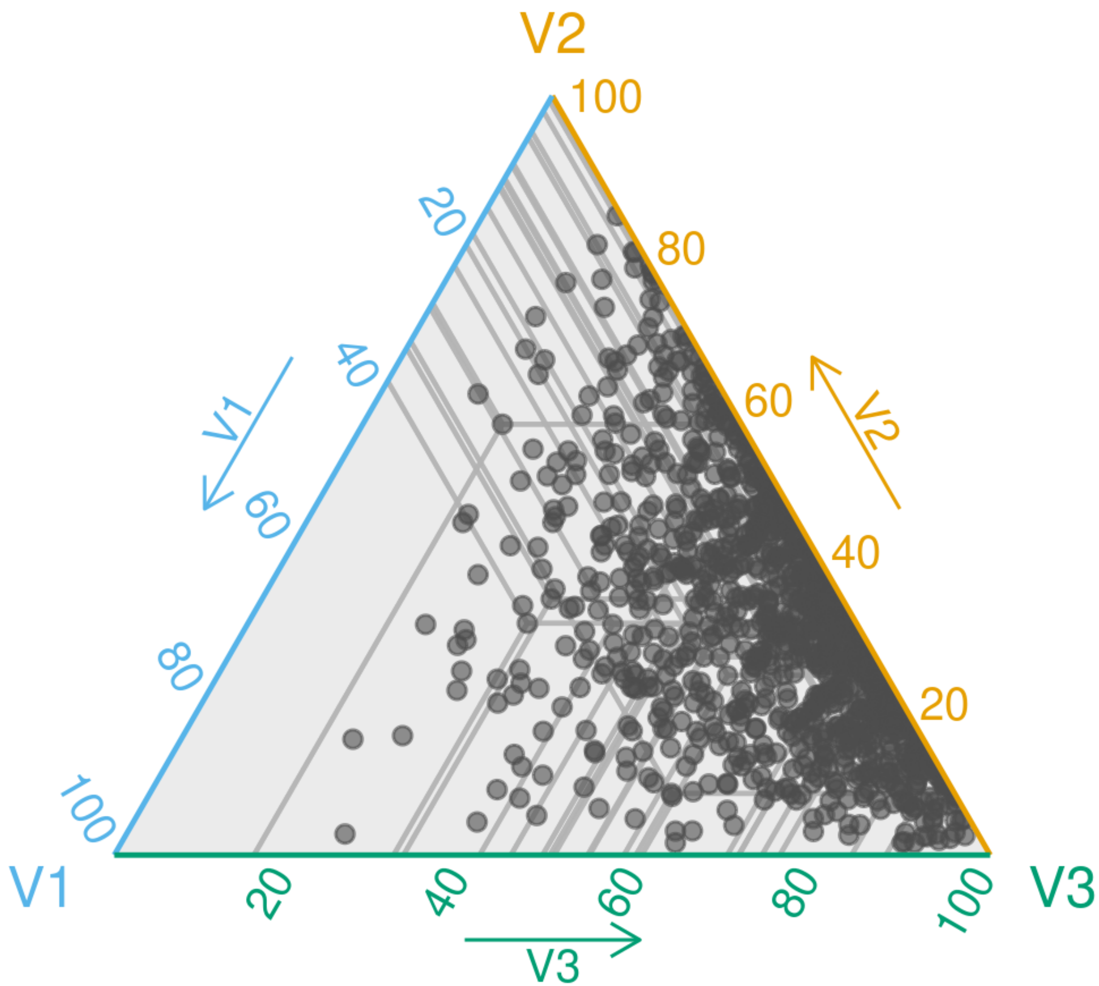
Step 2: Sample sector shares from Dirichlet distribution: $x_1, x_2, \ldots, x_K \sim Dir(\boldsymbol{\alpha}, \gamma = \hat{\gamma})$

Step 3: Multiply both $y_i = x_i y_0 \;\forall\; i \in 1, \ldots, K$

Sampling from a Dirichlet distribution

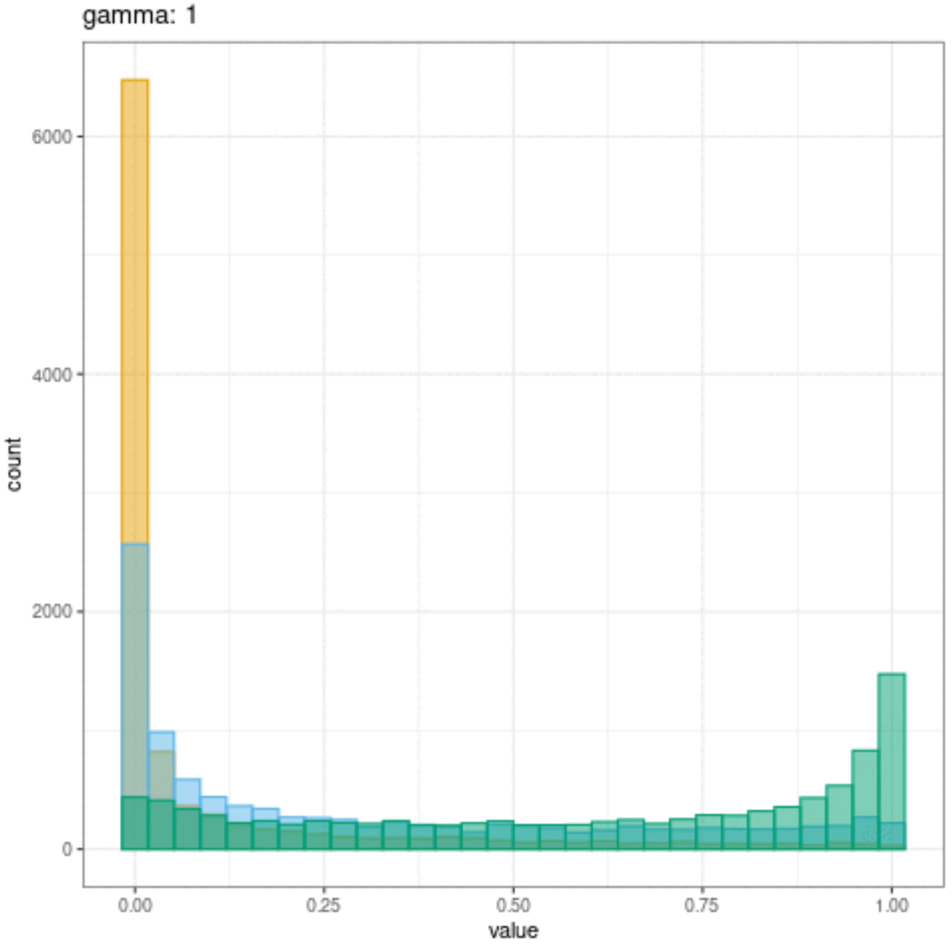


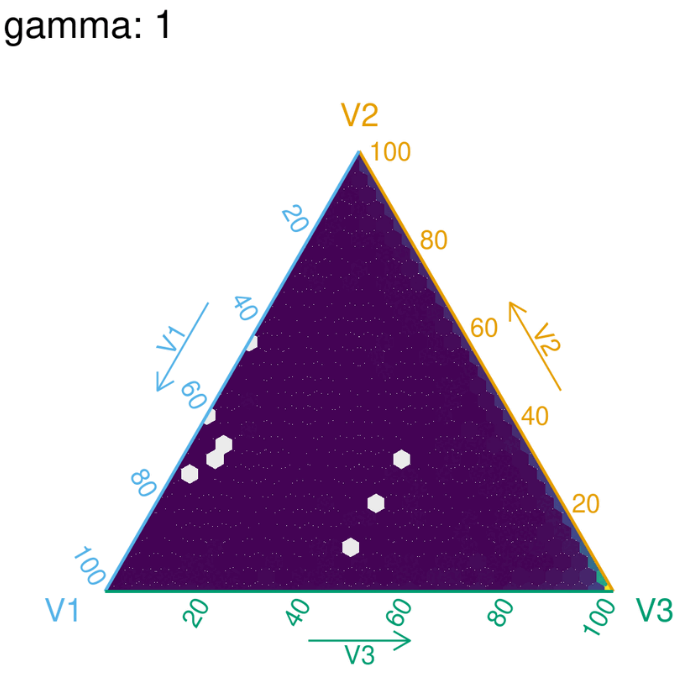
Sampling from a Dirichlet distribution



The γ parameter

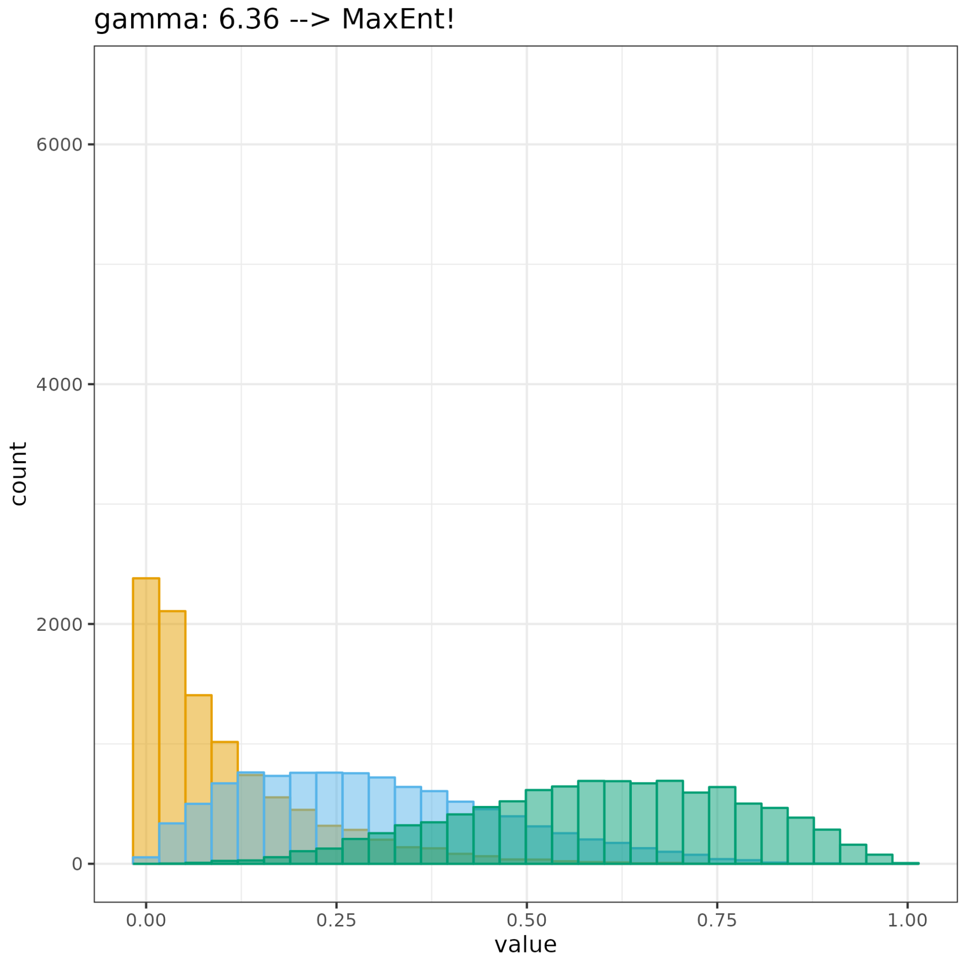
$x_1, x_2, \ldots, x_K \sim Dir(\boldsymbol{\alpha}, \gamma)$





The γ parameter

$$x_1, x_2, \ldots, x_K \sim Dir(\boldsymbol{\alpha}, \gamma = \hat{\gamma})$$



Maximum Entropy (MaxEnt) principle:
The least informative probability distribution consistent with a given set of constraints is the one which maximizes the entropy [11]

Finding $\hat{\gamma}$ which maximises the entropy

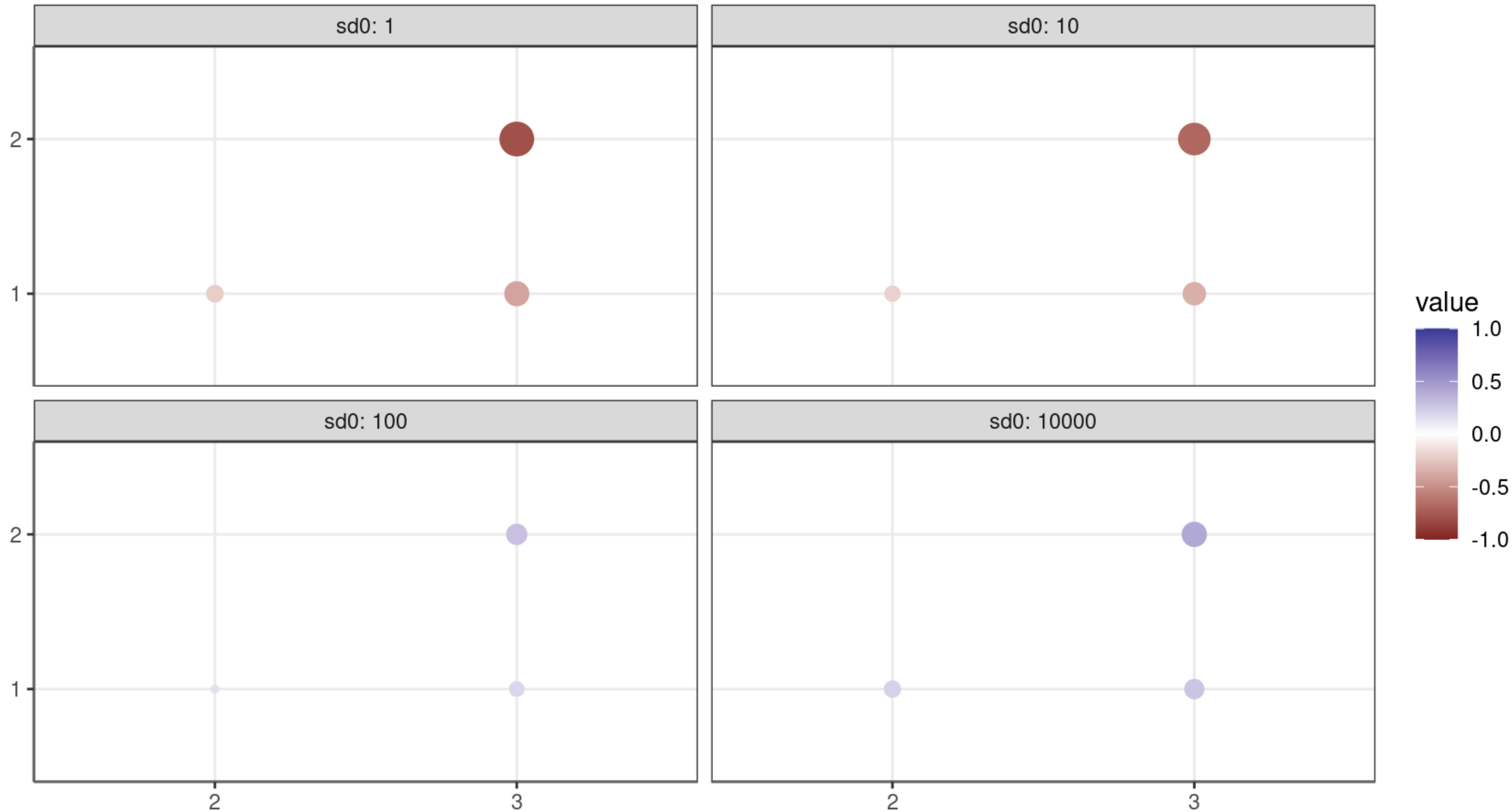
$x_1, x_2, \ldots, x_K \sim Dir(\boldsymbol{\alpha}, \gamma = \hat{\gamma})$

$$\max_{\gamma > 0} \; h(\gamma) = lnB(\gamma\boldsymbol{\alpha}) + (\gamma\alpha_0 - K)\psi(\gamma\alpha_0) - \sum_{i=1}^{K}(\gamma\alpha_i - 1)\psi(\gamma\alpha_i),$$

where

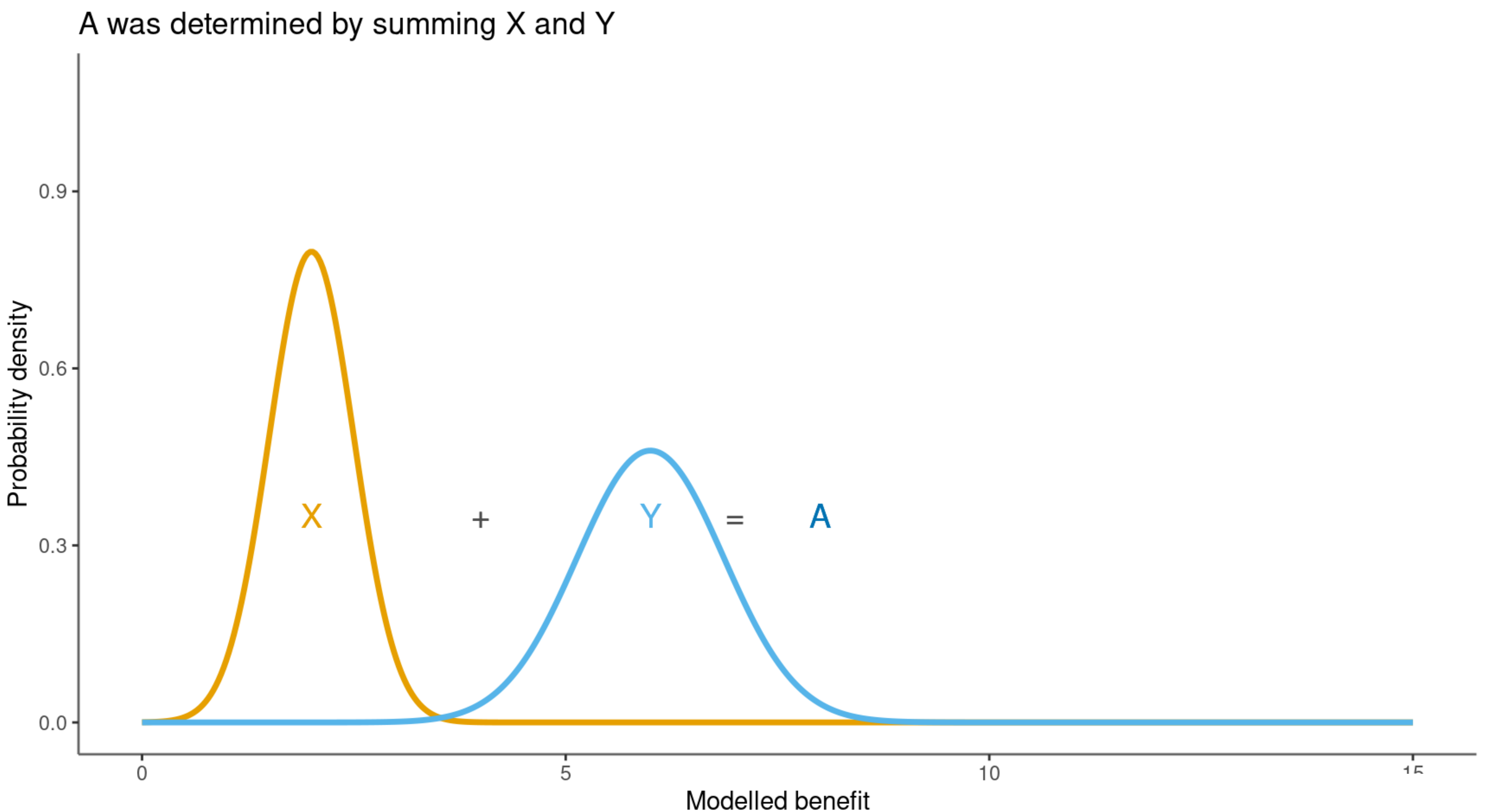
- $\psi(x)$ is the Digamma function $\psi(x) = \frac{d}{dn} ln(\Gamma(x)) = \frac{\Gamma'(x)}{\Gamma(x)}$,
- $\Gamma(x)$ is the Gamma function: $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$,
- $B(\gamma\boldsymbol{\alpha})$ is the multivariate beta function: $B(\gamma\boldsymbol{\alpha}) = \frac{\prod_{i=1}^{K} \Gamma(\gamma\alpha_i)}{\Gamma(\sum_{i=1}^{K} \gamma\alpha_i)}$

Correlations

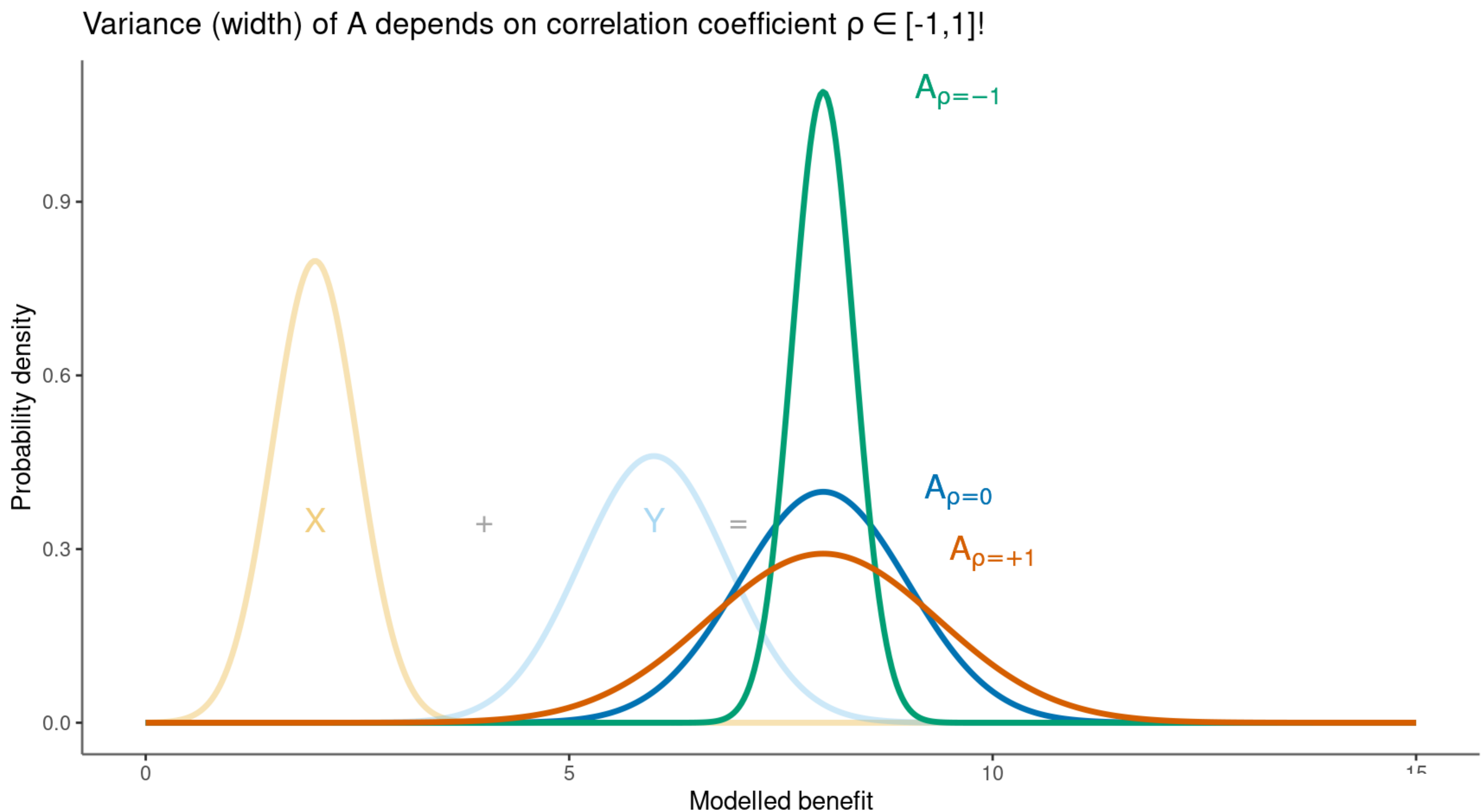


universität freiburg

Why correlations matter

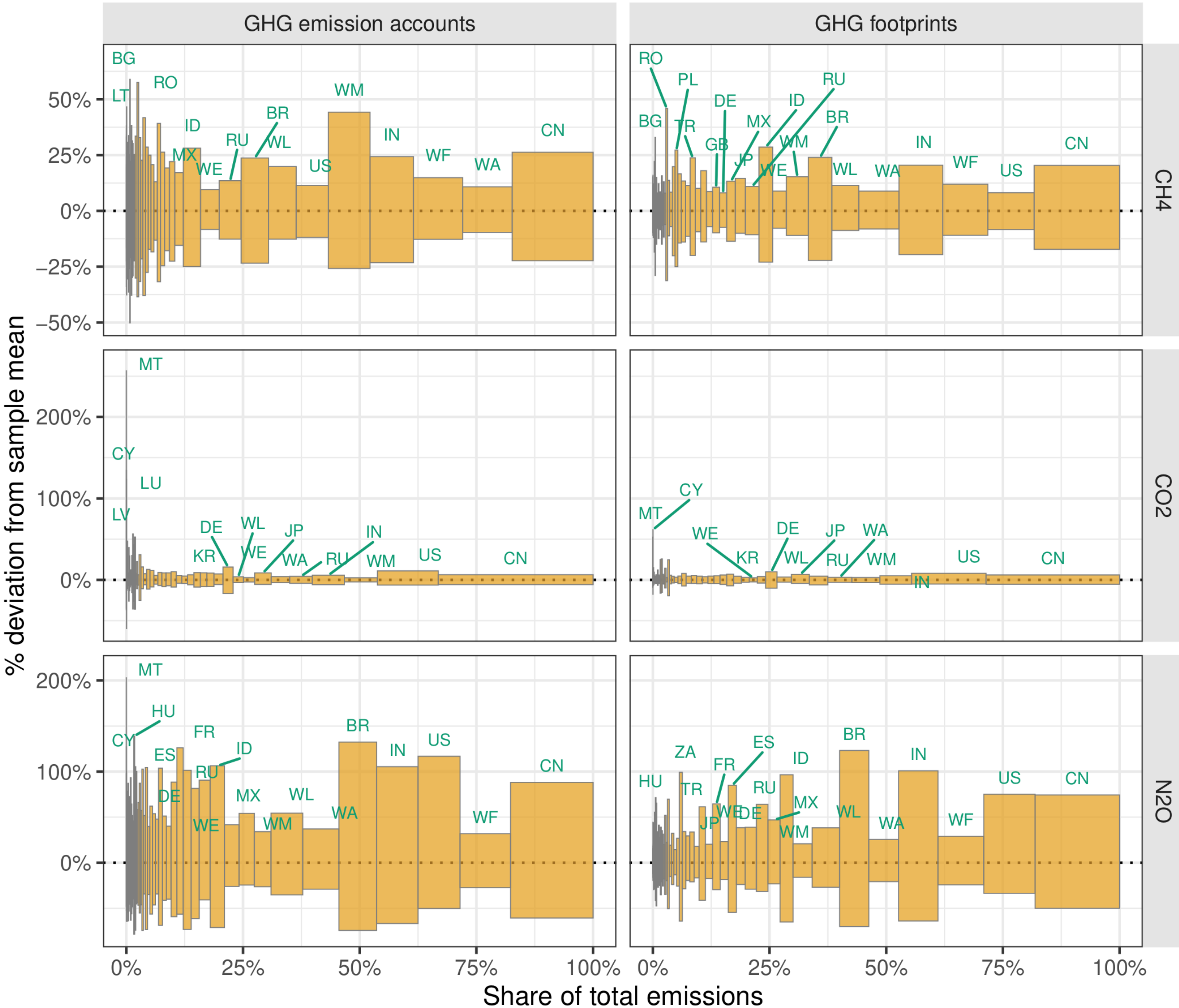


Why correlations matter

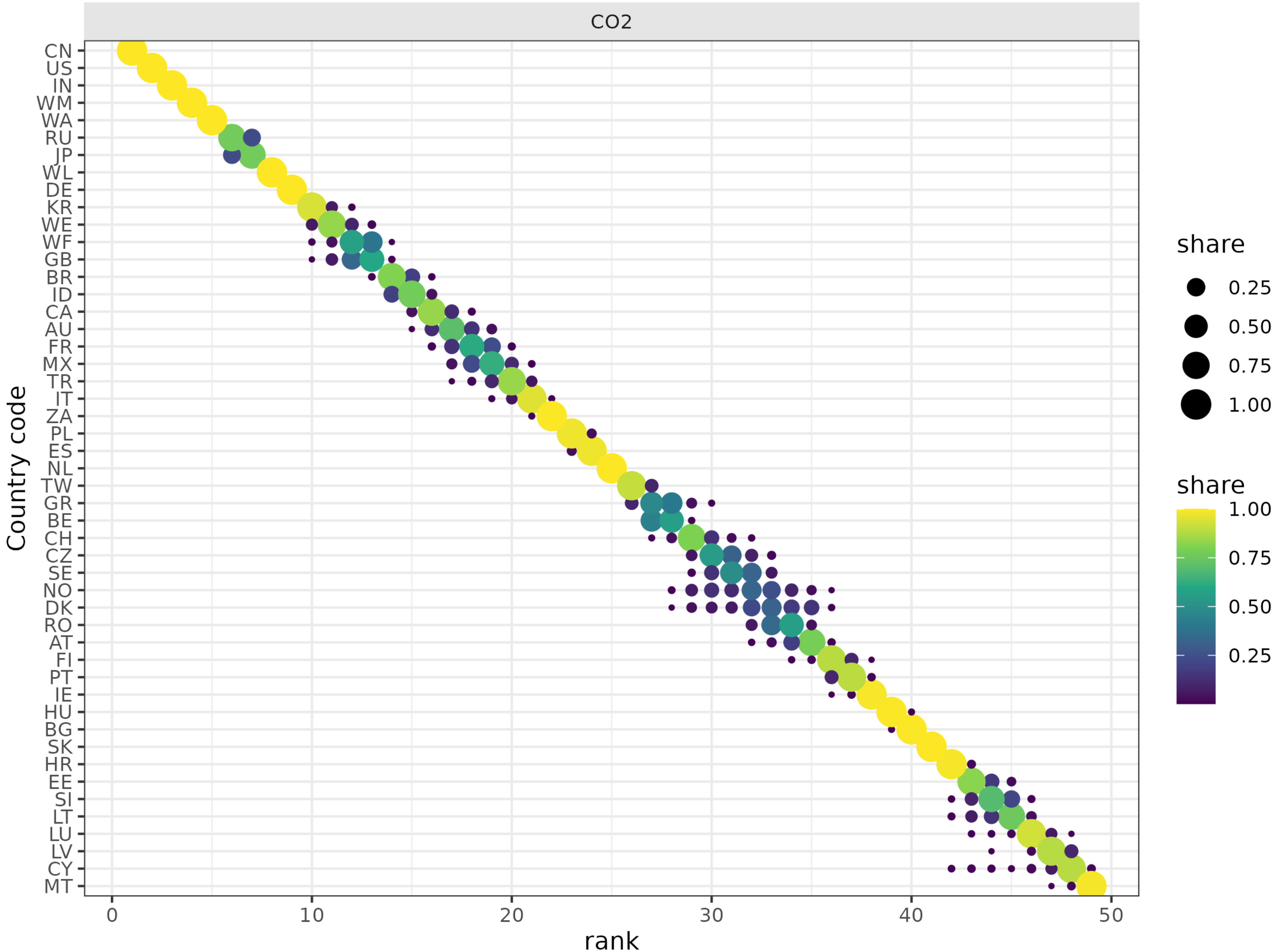


universität freiburg

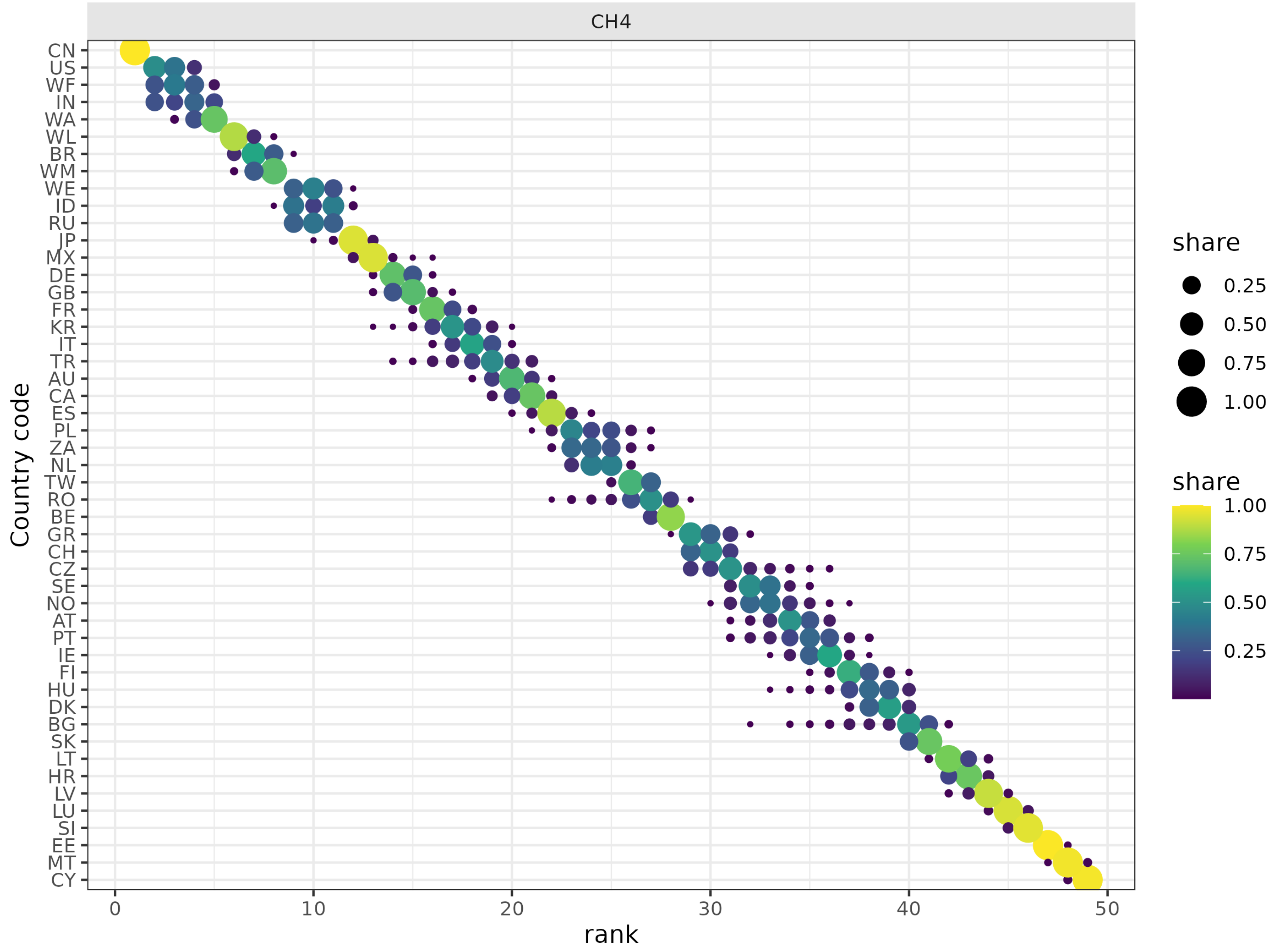
Results: Country level



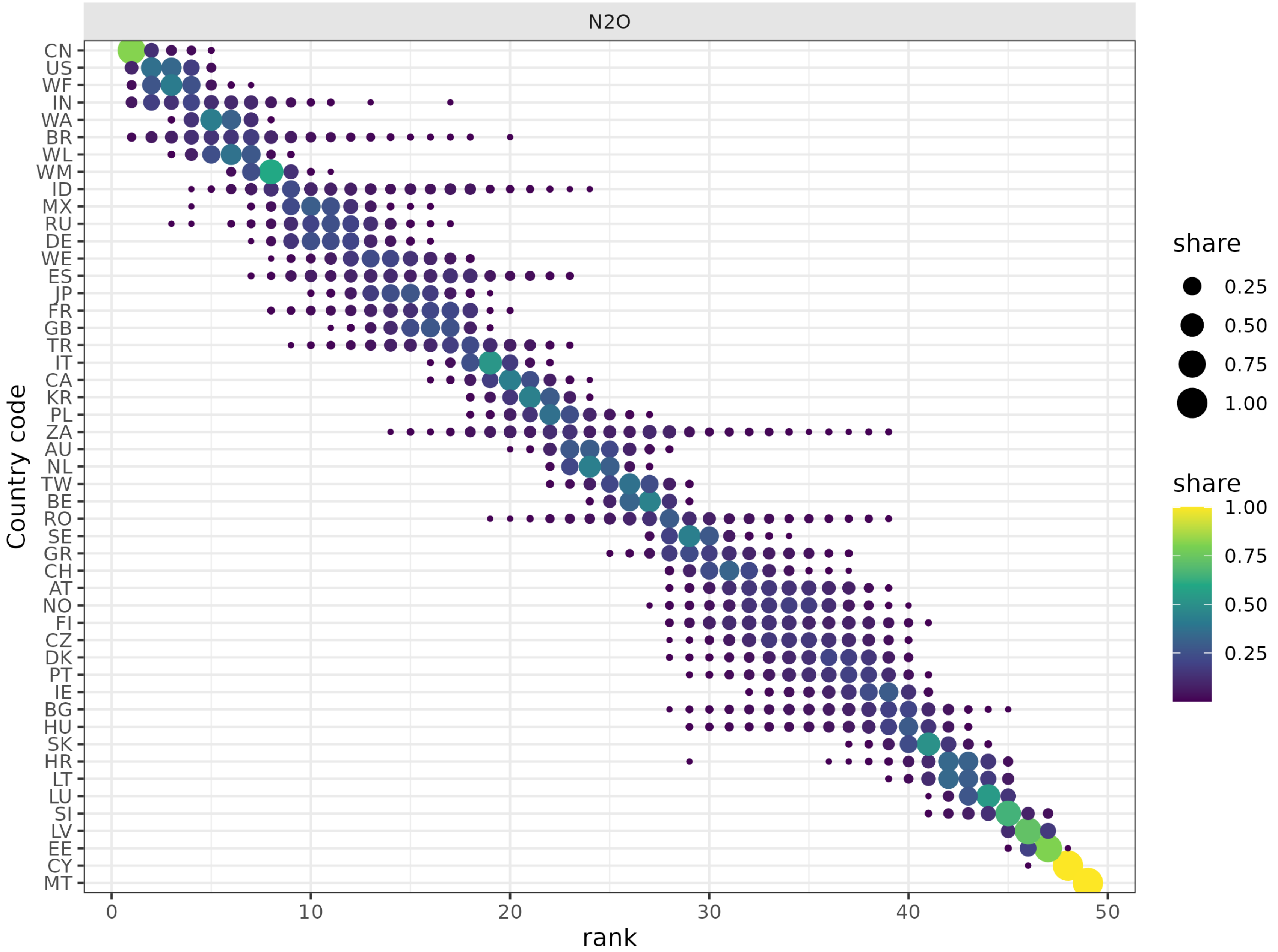
GHG emission accounts
GHG footprints
CH4
CO2
N2O
% deviation from sample mean
Share of total emissions
0%
25%
50%
75%
100%
50%
25%
0%
–25%
–50%
200%
100%
BG
LT
RO
ID
MX
WE
RU
BR
WL
US
WM
IN
WF
WA
CN
PL
DE
TR
GB
JP
MT
CY
LU
LV
KR
HU
ES
FR
ZA



universität freiburg

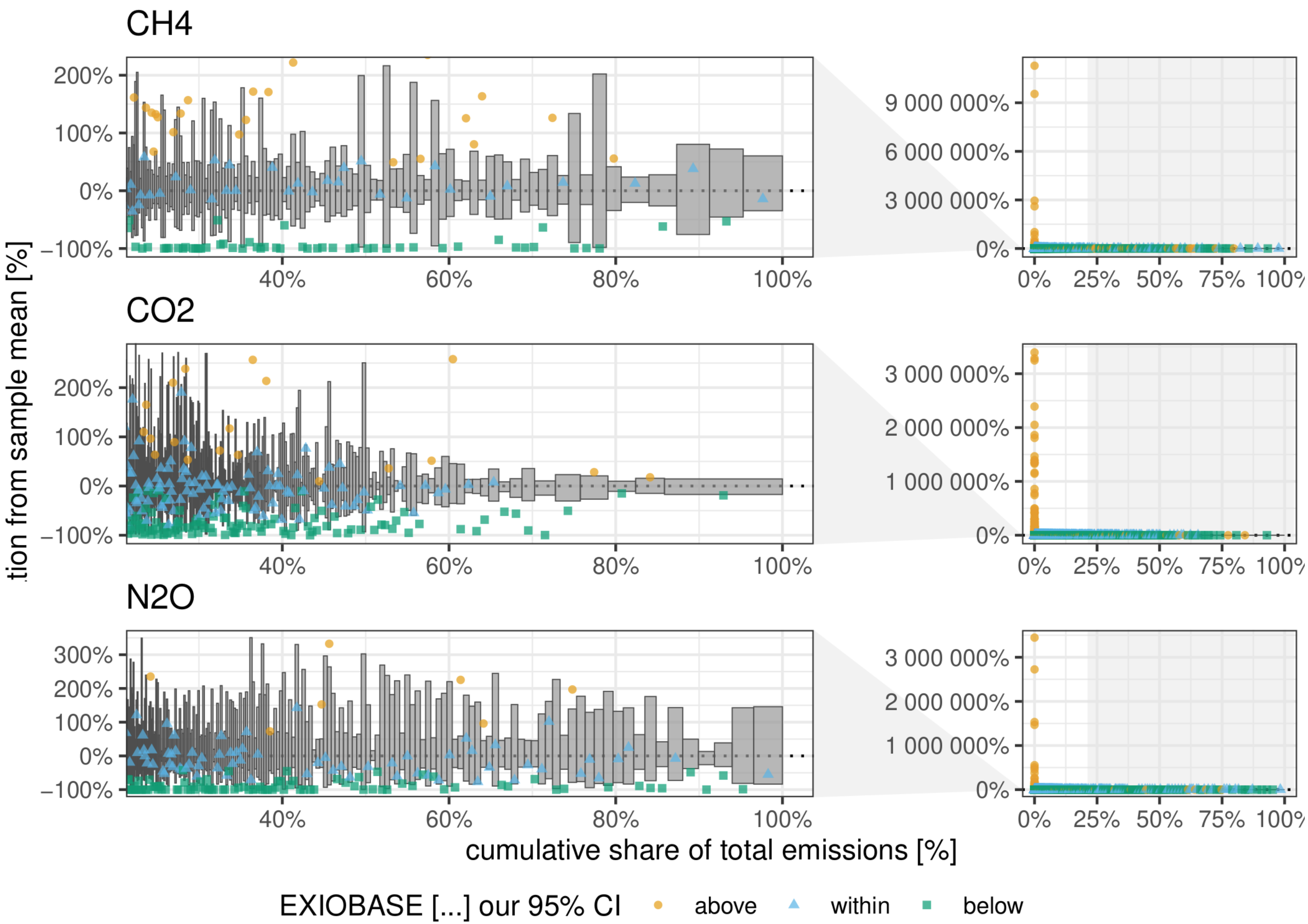


universität freiburg

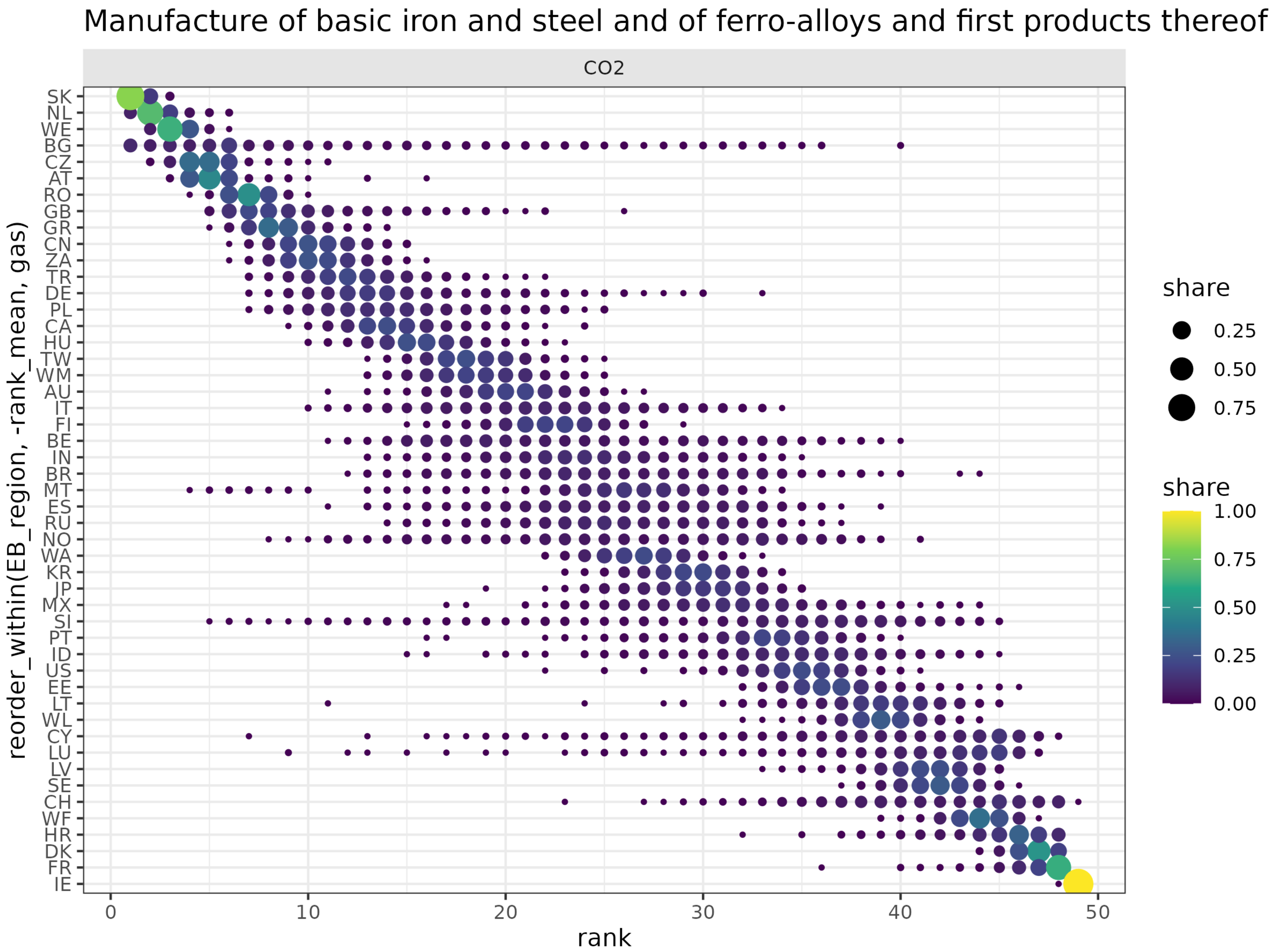


universität freiburg

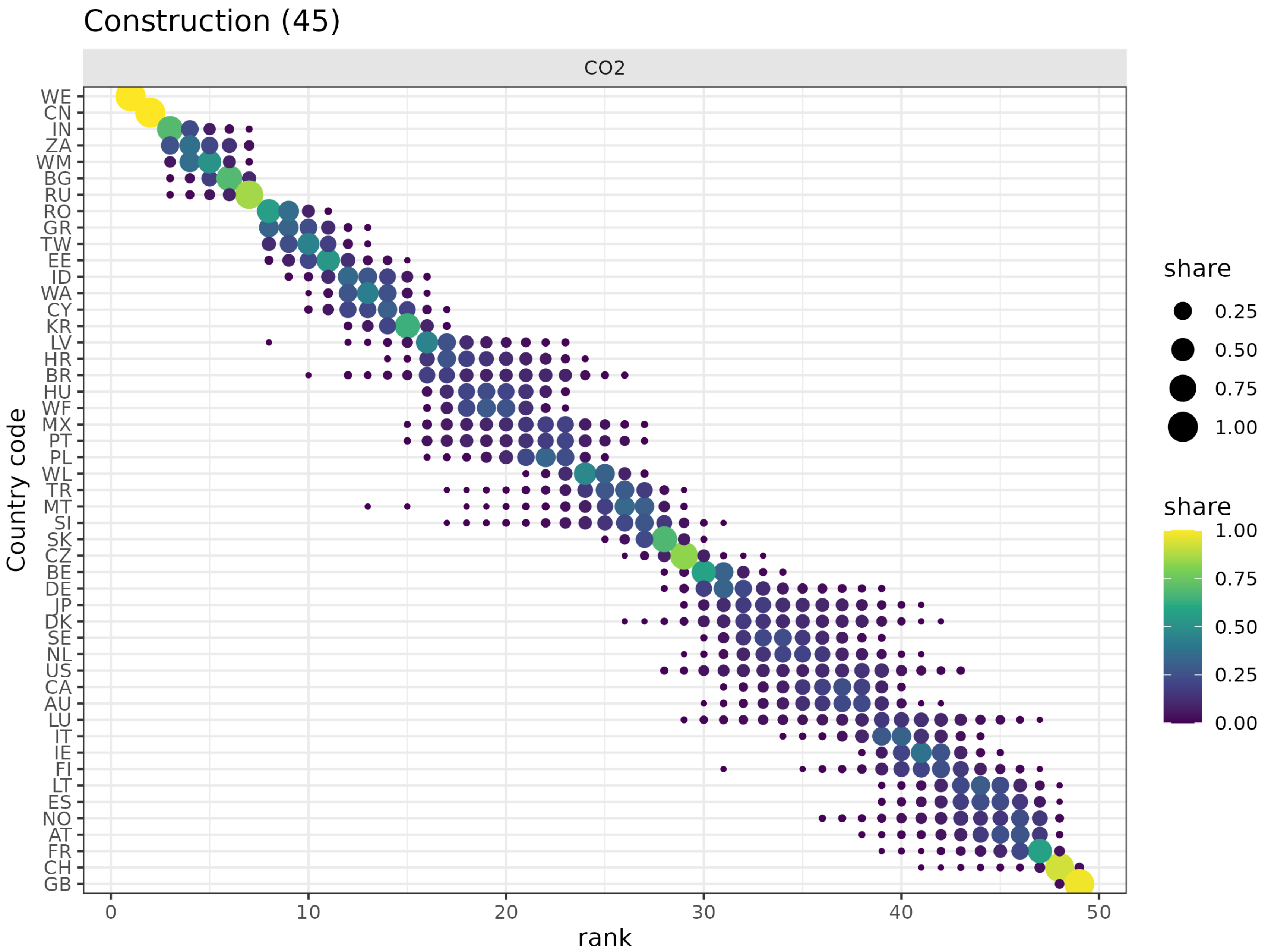
Results: Sector level



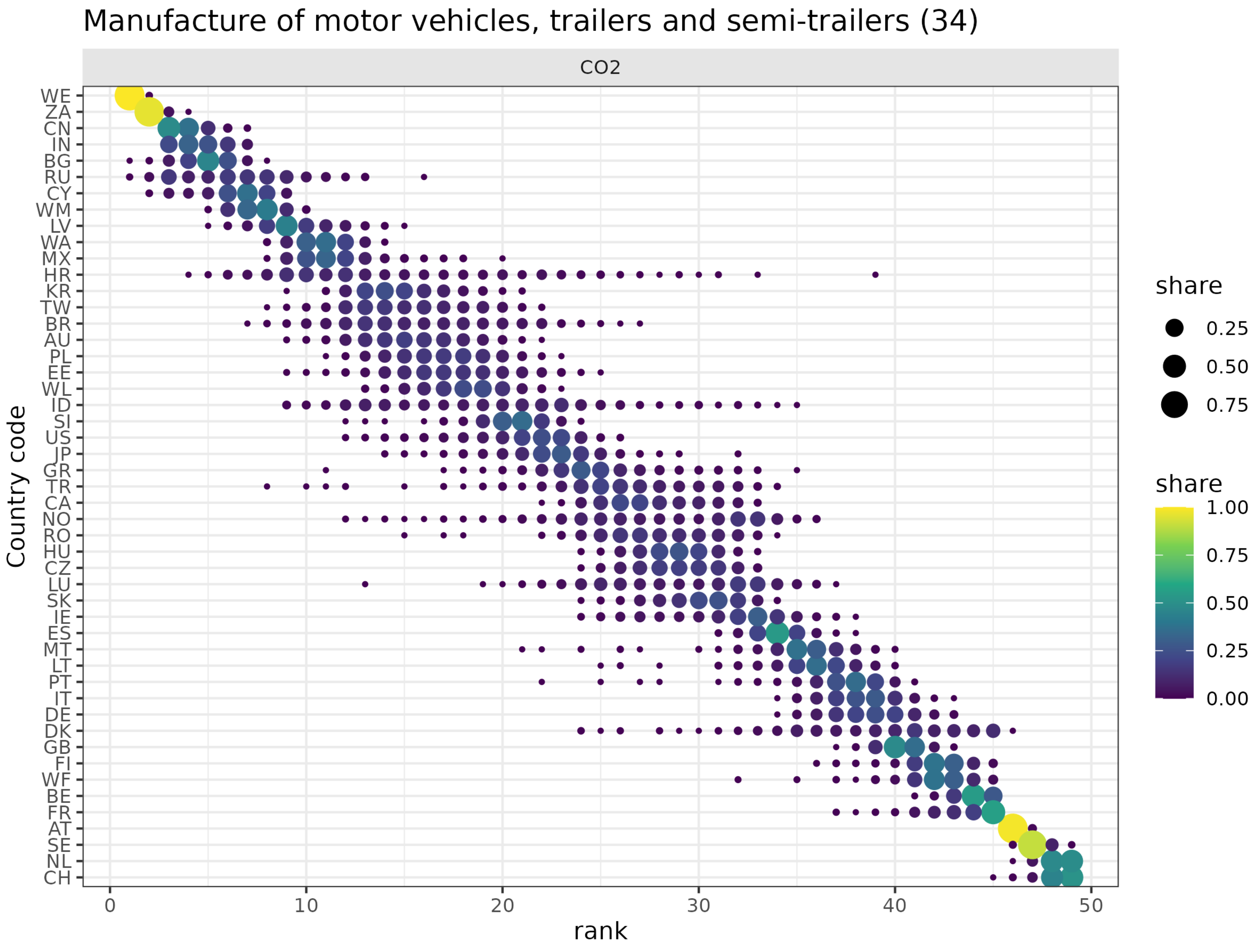
universität freiburg



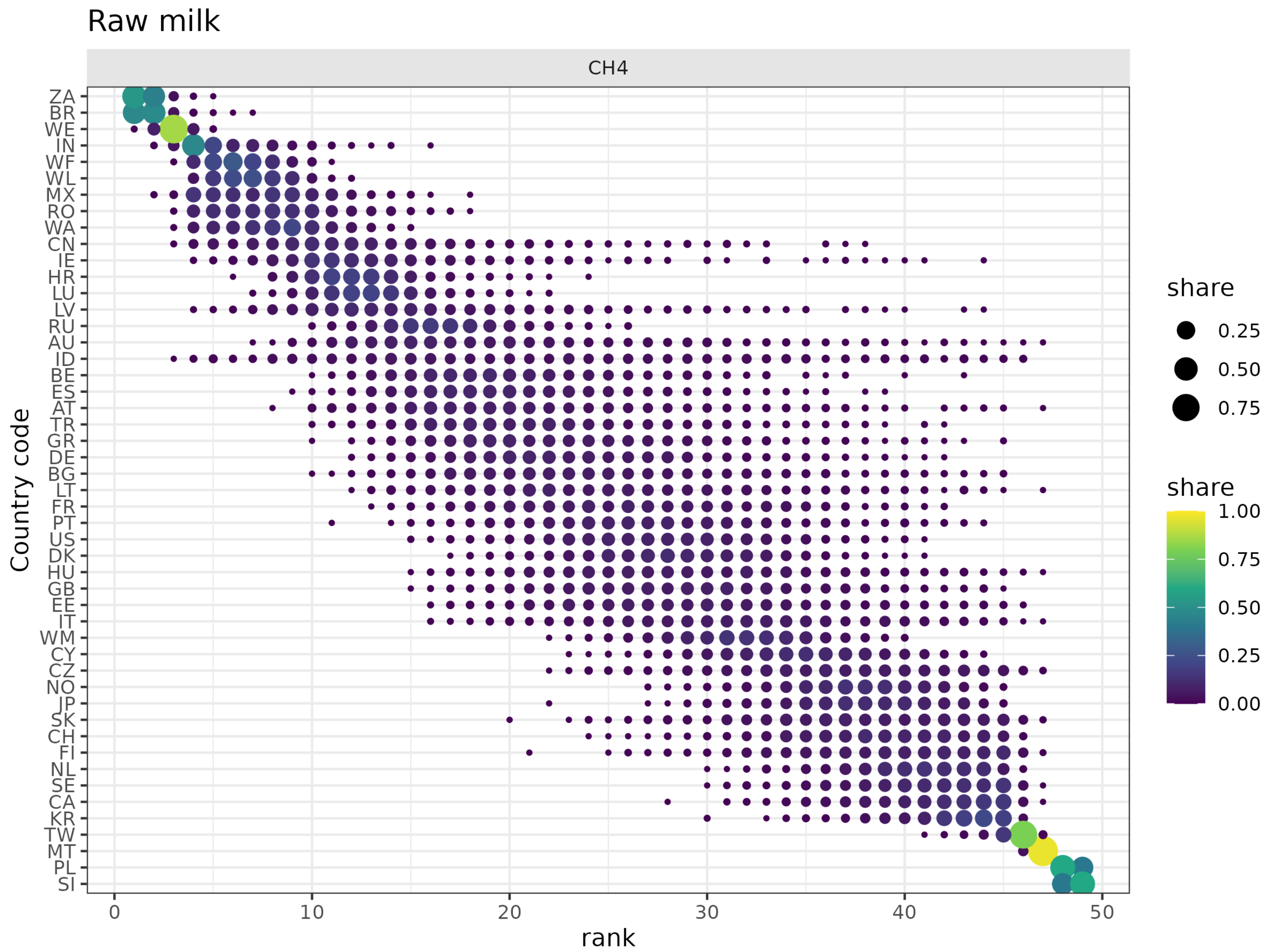
universität freiburg



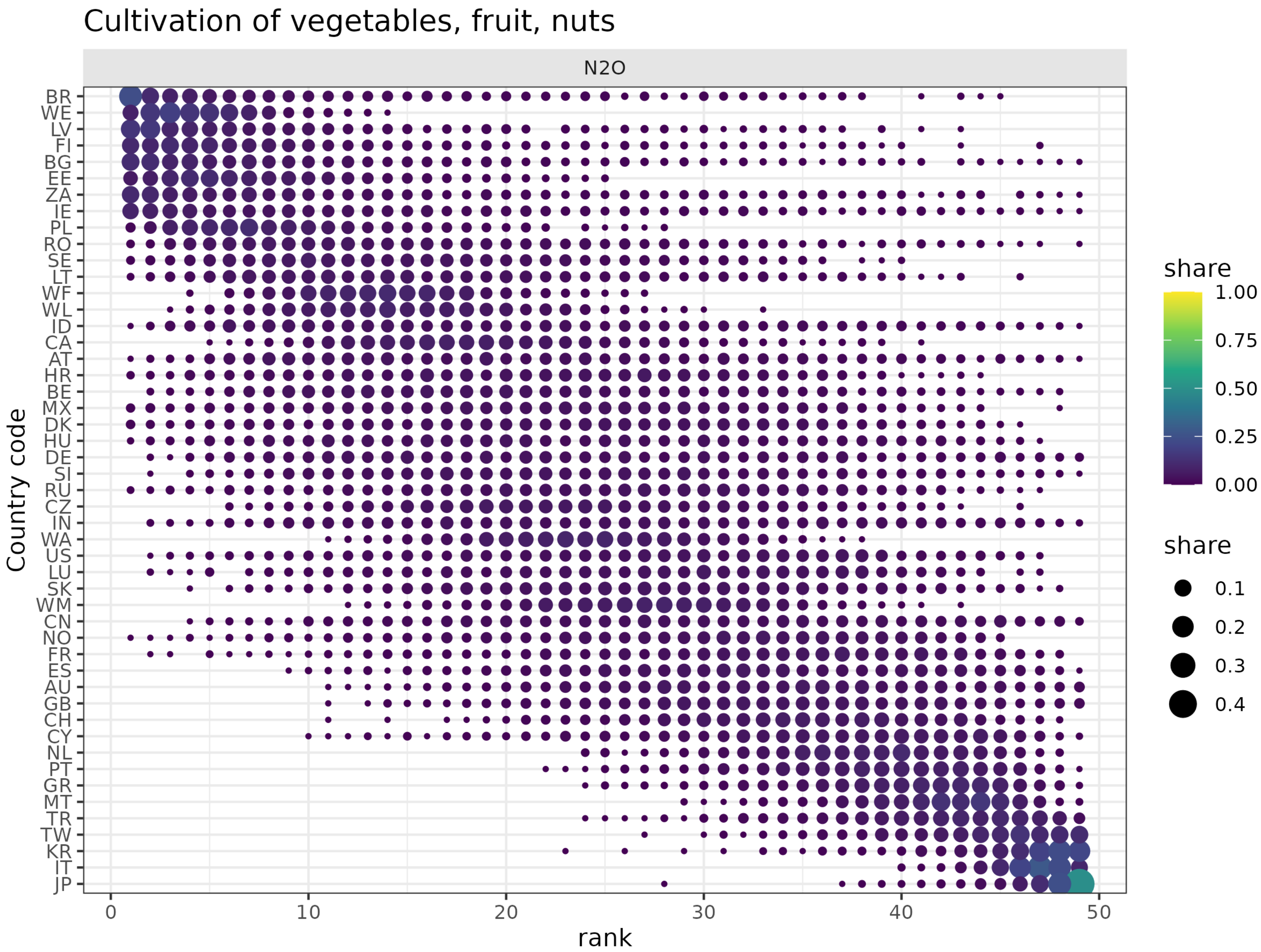
universität freiburg



universität freiburg

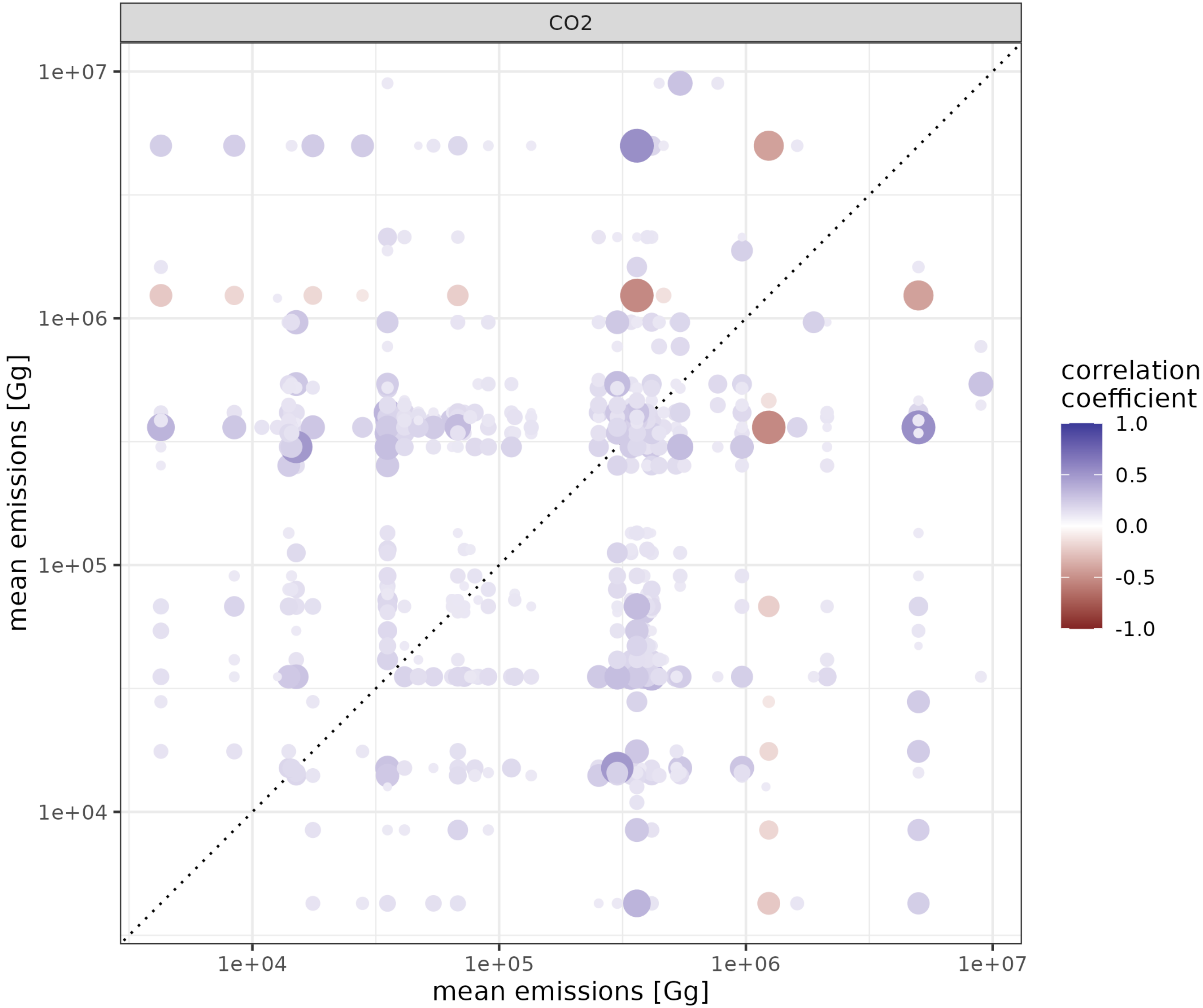


universität freiburg

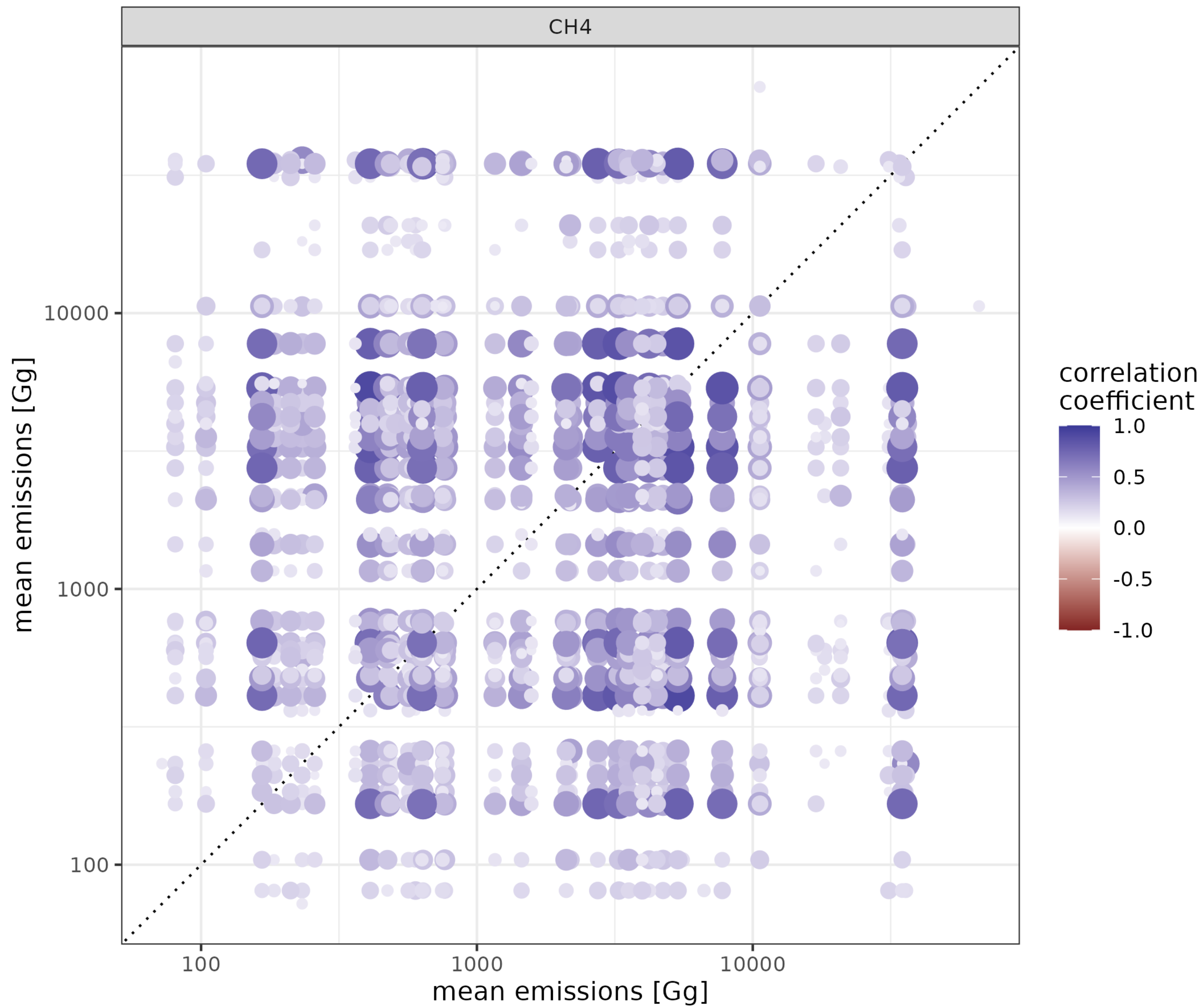


universität freiburg

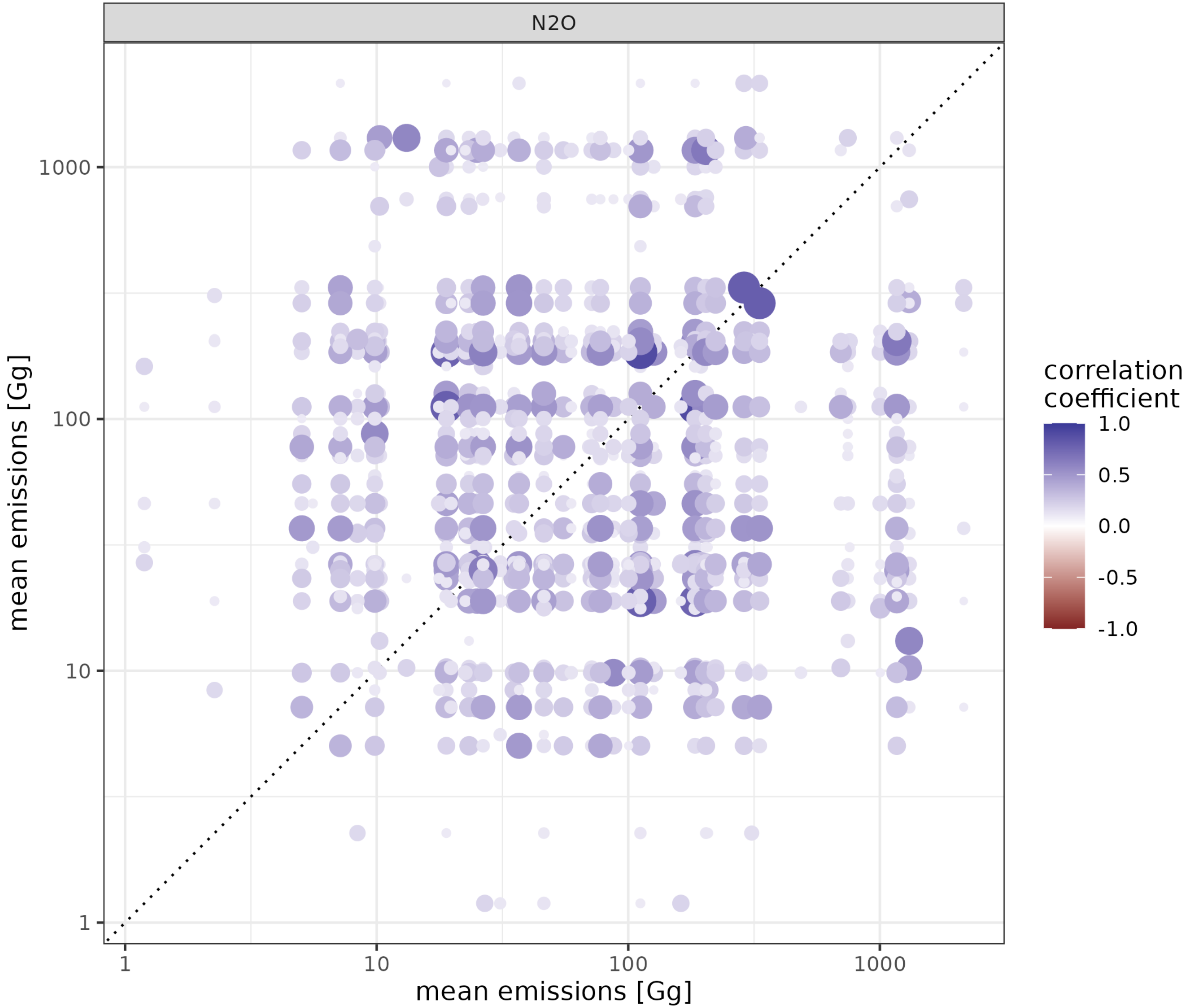
Results: Correlations



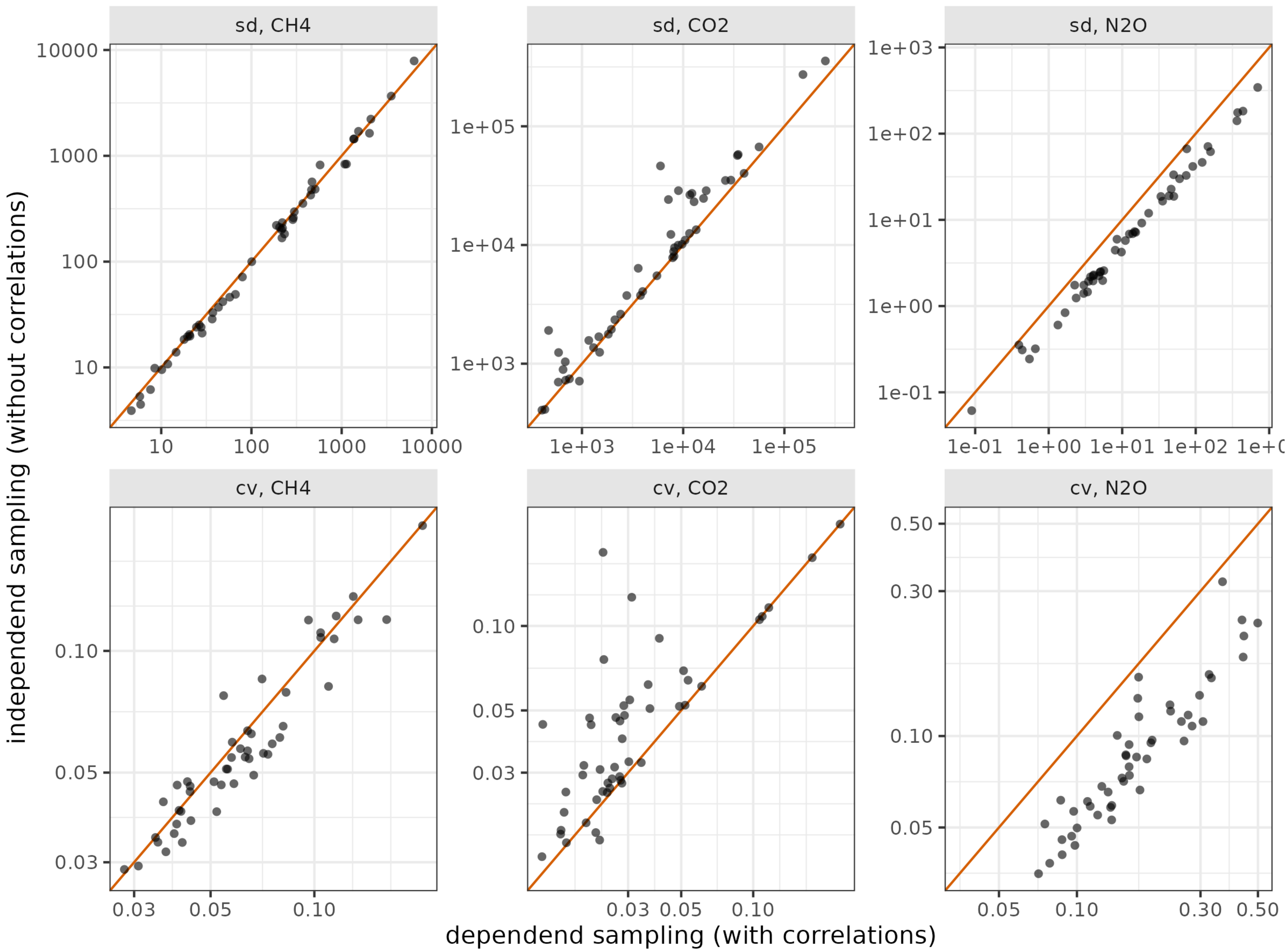
universität freiburg



universität freiburg



universität freiburg



sd, CH4
sd, CO2
sd, N2O
cv, CH4
cv, CO2
cv, N2O
independend sampling (without correlations)
dependend sampling (with correlations)
10000
1000
100
10
1e+05
1e+04
1e+03
1e+02
1e+01
1e+00
1e-01
0.10
0.05
0.03
0.50
0.30
1e-01
1e+00
1e+01
1e+02
1e+05
1e+04
1e+03
0.10
0.05
0.03
0.10
0.05
0.30
0.50

Conclusion

- Uncertainty hot-spots:
  - National level:
    - CO_2: small economies subject to large residence adjustments
    - In general larger uncertainties for CH_4 and esp. N_2O
  - Sector level: Overall: high uncertainties (median CV of ~1)
- Ignoring correlations would *overestimate* CO_2-footprints and *underestimate* N_2O-footprints

- Open science:
  - Preprint: https://essd.copernicus.org/preprints/essd-2023-473/
  - Code: https://github.com/simschul/uncertainty_GHG_accounts
  - Results data: https://zenodo.org/records/10041196
  - UNFCCC uncertainties: https://zenodo.org/records/10037714

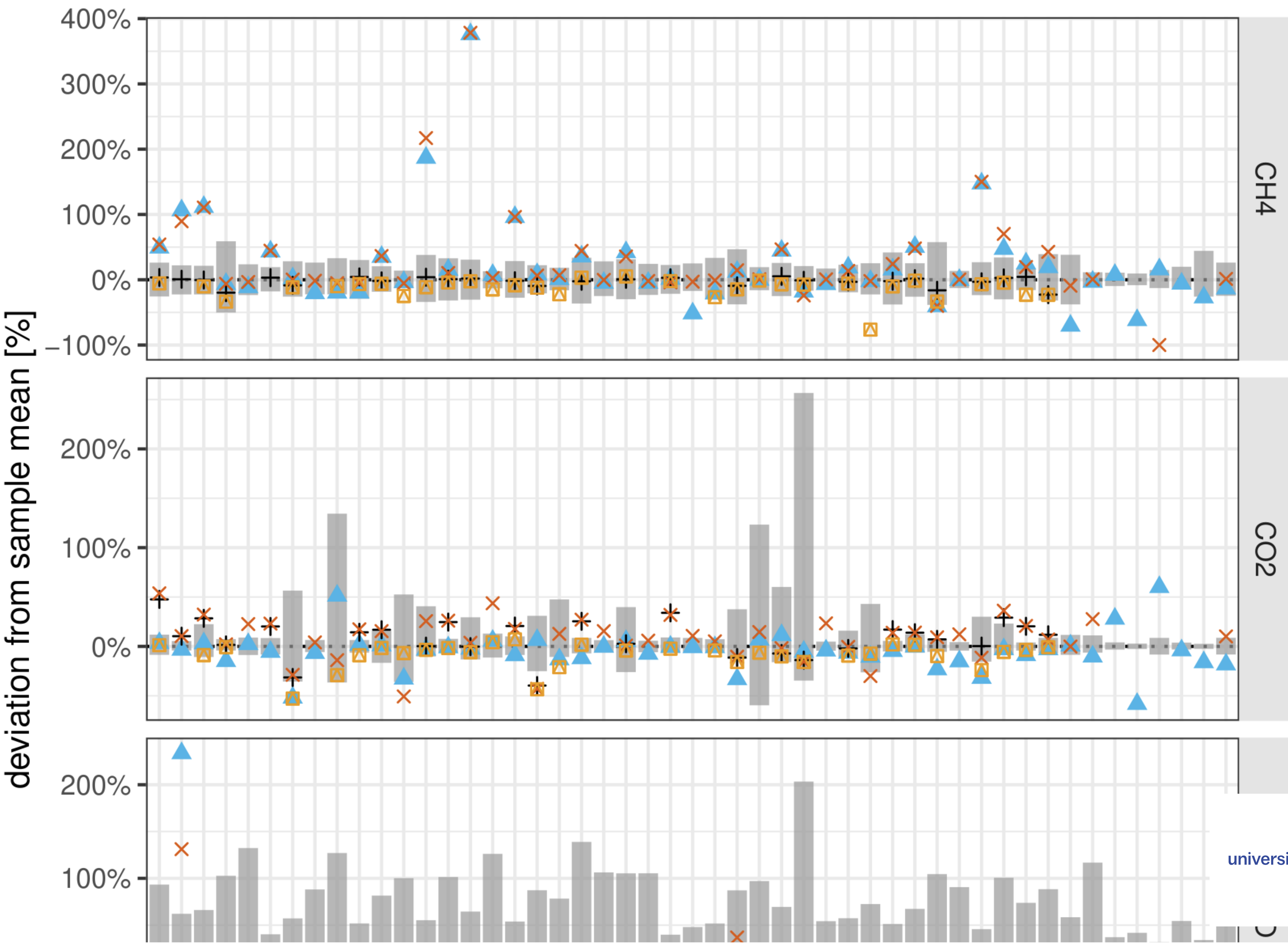
Thank you!

References

1. M. Lenzen, R. Wood, & T. Wiedmann, Uncertainty Analysis for Multi-Region Input–Output Models – a Case Study of the Uk's Carbon Footprint. *Economic Systems Research*, **22** (2010) 43–63. https://doi.org/10.1080/09535311003661226.
2. H. C. Wilting, Sensitivity and uncertainty analysis in mrio modelling; some empirical results with regard to the dutch carbon footprint. *Economic Systems Research*, **24** (2012) 141–171. https://doi.org/10.1080/09535314.2011.628302.
3. J. Karstensen, G. P. Peters, & R. M. Andrew, Uncertainty in temperature response of current consumption-based emissions estimates. *Earth System Dynamics*, **6** (2015) 287–309. https://doi.org/10.5194/esd-6-287-2015.
4. D. Moran, K. Kanemoto, M. Jiborn, R. Wood, J. Többen, & K. C. Seto, Carbon footprints of 13000 cities. *Environmental Research Letters*, **13** (2018) 064041. https://doi.org/10.1088/1748-9326/aac72a.
5. P. Shrestha & C. Sun, Carbon emission flow and transfer through international trade of forest products. *Forest Science*, **65** (2019) 439–451. https://doi.org/10.1093/forsci/fxz003.
6. H. Zhang, K. He, X. Wang, & E. G. Hertwich, Tracing the Uncertain Chinese M Footprint within the Global Supply Chain Using a Stochastic, Nested Input-

Model. *Environmental Science & Technology*, **53** (2019) 6814–6823. https://doi.org/10.1021/acs.est.8b06373.

7. K. Kanemoto, Y. Shigetomi, N. T. Hoang, K. Okuoka, & D. Moran, Spatial variation in household consumption-based carbon emission inventories for 1200 Japanese cities. *Environmental Research Letters*, **15** (2020) 114053. https://doi.org/10.1088/1748-9326/abc045.
8. K. Abbood, G. Egilmez, & F. Meszaros, Multi-region Input-Output-based Carbon and Energy Footprint Analysis of U.S. Manufacturing. *Periodica Polytechnica Social and Management Sciences*, **31** (2023) 91–99. https://doi.org/10.3311/PPso.19554.
9. M. Lenzen, D. Moran, K. Kanemoto, & A. Geschke, Building eora: A global multi-region inputoutput database at high country and sector resolution. *Economic Systems Research*, **25** (2013) 20–49. https://doi.org/10.1080/09535314.2013.769938.
10. M. Lenzen, A. Geschke, J. West, J. Fry, A. Malik, S. Giljum, L. Milà i Canals, P. Piñero, S. Lutter, T. Wiedmann, M. Li, M. Sevenster, J. Potočnik, I. Teixeira, M. Van Voore, K. Nansai, & H. Schandl, Implementing the material footprint to measure progress towards Sustainable Development Goals 8 and 12. *Nature Sustainability*, **5** (2022) 157–166. https://doi.org/10.1038/s41893-021-00811-6.
11. E. T. Jaynes, Information Theory and Statistical Mechanics. *Physical Review*, **106** (1957) 620–630. https://doi.org/10.1103/PhysRev.106.620.



400%
300%
200%
100%
0%
−100%
CH4
200%
100%
0%
CO2
200%
100%
deviation from sample mean [%]