What **range** could your **causal effect** lie between if the instrumental variable assumptions held?

Find out with our **bpbounds R package** and **Shiny app**!

bpbounds: R package and web app

Tom Palmer [1,]

tom.palmer@lancaster.ac.uk

Roland Ramsahai Vanessa Didelez[2] Nuala Sheehan[3]

[1] *Department of Mathematics and Statistics, Lancaster University*

[2] *Leibniz BIPS, Bremen, Germany*

[3] *Department of Health Sciences, University of Leicester*

Introduction

- We present our bpbounds R package and Shiny web app for the nonparametric bounds for the average causal effect (ACE) due to Balke and Pearl **(Palmer et al. 2018)**.
- This is an R implementation of our Stata programs **(Palmer et al. 2011)**.
- The package can be installed from CRAN as follows:

```
install.packages("bpbounds")
```

- Code development is on the GitHub repository: https://github.com/remlapmot/bpbounds

Methods

- Under the instrumental variable assumptions alone, without additional parametric model assumptions, the ACE is not identified.
- **Balke and Pearl (1997)** showed it is possible to derive bounds for the ACE.
- The bounds have the following interpretation:

  There is some joint distribution of the unobserved confounders and the observed variables that yields a true ACE as small as the lower bound, while another choice produces an ACE as large as the upper bounds (the bounds are tight).

- There are at least two ways to implement the Balke-Pearl bounds:

  i. using conditional probabilities calculated from contingency tables;
  ii. the polytope method due to **Dawid (2003)**.

- We implemented the polytope method since it is generalisable for identified IV models with exposures, outcomes, and instruments with more than 2 categories.
- Currently, we allow for a binary or 3 category instrument, and binary exposure and outcome.

Example Mendelian randomization analysis

- We extract an example from **Meleady et al. (2003)**.
- We have a 3 category instrument and binary exposure and outcome.
- We use the 677CT polymorphism (rs1801133) in the MTHFR gene, involved in folate metabolism, as an instrumental variable to investigate the causal effect of homocysteine on the risk of cardiovascular disease.
- The code is shown on the right.
- The ACE lies between a risk difference of -9% to 74% increase in absolute risk.
- Additionally, we see that the monotonicity inequality is not satisfied.

Conclusion

- Use of bounds in instrumental variable analyses is regaining interest **(Swanson et al. 2018; Labrecque and Swanson 2018)**.
- The empirical experience that the bounds are often wide is not a bad property of the method, it is a property of the typical data: Mendelian randomization data simply often are uninformative in that sense due to weak instrumental variables.
- We recommend using the bounds when the variables are genuinely discrete, but not when the exposure is genuinely continuous **(Sheehan and Didelez 2019)**.
- Our R package and app provide a convenient interface to the bounds.

References

Balke, A., and J. Pearl. 1997. "Bounds on treatment effects from studies with imperfect compliance." *Journal of the American Statistical Association* 92 (439): 1172–6. https://doi.org/10.1080/01621459.1997.10474074.

Dawid, A. P. 2003. "Causal Inference Using Influence Diagrams: The Problem of Partial Compliance (with Discusssion)." In *Highly Structured Stochastic Systems*, edited by P. J. Green, N. L. Hjort, and S. Richardson, 45–65. New York: Oxford University Press.

Labrecque, Jeremy, and Sonja A Swanson. 2018. "Understanding the Assumptions Underlying Instrumental Variable Analyses: A Brief Review of Falsification Strategies and Related Tools." *Current Epidemiology Reports* 5 (3): 214–20. https://doi.org/10.1007/s4047.

Meleady, Raymond, Per M Ueland, Henk Blom, Alexander S Whitehead, Helga Refsum, Leslie E Daly, Stein Emil Vollset, et al. 2003. "Thermolabile Methylenetetrahydrofolate Reductase, Homocysteine, and Cardiovascular Disease Risk: The European Concerted Action Project." *The American Journal of Clinical Nutrition* 77 (1): 63–70. https://doi.org/10.1093/ajcn/77.1.63.

Palmer, T. M., R. Ramsahai, V. Didelez, and N. A. Sheehan. 2018. *bpbounds: R package implementing Balke-Pearl bounds for the average causal effect*. https://CRAN.R-project.org/package=bpbounds.

Palmer, T. M., R. R. Ramsahai, V. Didelez, and N. A Sheehan. 2011. "Nonparametric Bounds for the Causal Effect in a Binary Instrumental-Variable Model." *Stata Journal* 11 (3): 345–67. http://www.stata-journal.com/article.html?article=st0232.

Sheehan, Nuala A, and Vanessa Didelez. 2019. "Epidemiology, genetic epidemiology and Mendelian randomisation: more need than ever to attend to detail." *Human Genetics*, 1–16. https://doi.org/10.1007/s00439-019-02027-3.

Swanson, Sonja A., Miguel A. Hernán, Matthew Miller, James M. Robins, and Thomas S. Richardson. 2018. "Partial Identification of the Average Treatment Effect Using Instrumental Variables: Review of Methods for Binary Instruments, Treatments, and Outcomes." *Journal of the American Statistical Association* 113 (522): 933–47. https://doi.org/10.1080/01621459.2018.1434530.

Extra Figures & Tables

```
library(bpbounds)
mt3 <- c(.83, .05, .11, .01,
         .88, .06, .05, .01,
         .72, .05, .20, .03)
p3 <- array(mt3, dim = c(2, 2, 3),
            dimnames = list(x = c(0, 1),
                            y = c(0, 1),
                            z = c(0, 1, 2)))
bpres3 <- bpbounds(as.table(p3))
summary(bpres3)
##
## Data:                      trivariate
## Instrument categories:     3
##
## Instrumental inequality: TRUE
##   Causal parameter Lower bound Upper bound
##                ACE       -0.09     0.74000
##        P(Y|do(X=0))       0.06     0.12000
##        P(Y|do(X=1))       0.03     0.80000
##                CRR        0.25    13.33333
##
## Monotonicity inequality: FALSE
```

Figure 1: Shiny app https://remlapmot.shinyapps.io/bpbounds

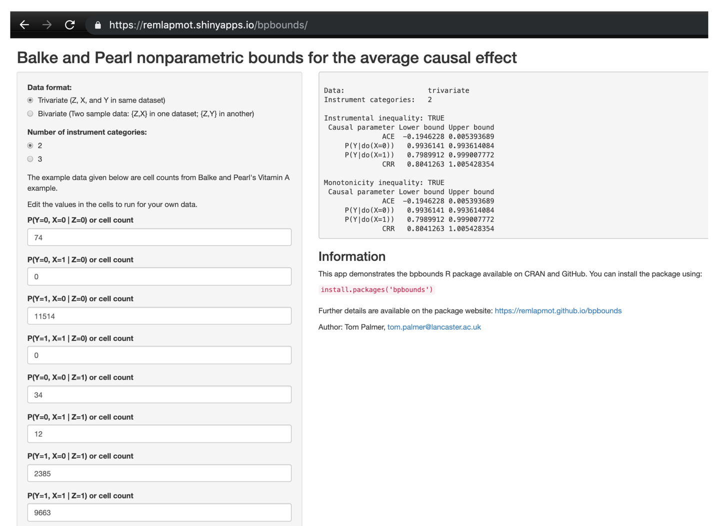

Figure 2: Screenshot of our Shiny app.

Figure 3: Package website https://remlapmot.github.io/bpbounds/