

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

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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:

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

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

Methods

- Balke and Pearl (1997) showed it is possible to derive bounds for the ACE.
- Bounds have the interpretation of:

There is some distribution of the unobserved confounders (of the exposure-outcome association) that yields a true ACE as small as the lower bound, while another choice produces an ACE as large as the upper bound.

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

- i. conditional probabilities 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 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 phenotype and outcomes.
- 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).
- Our R package and app provide a convenient interface to the bounds.

References

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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>

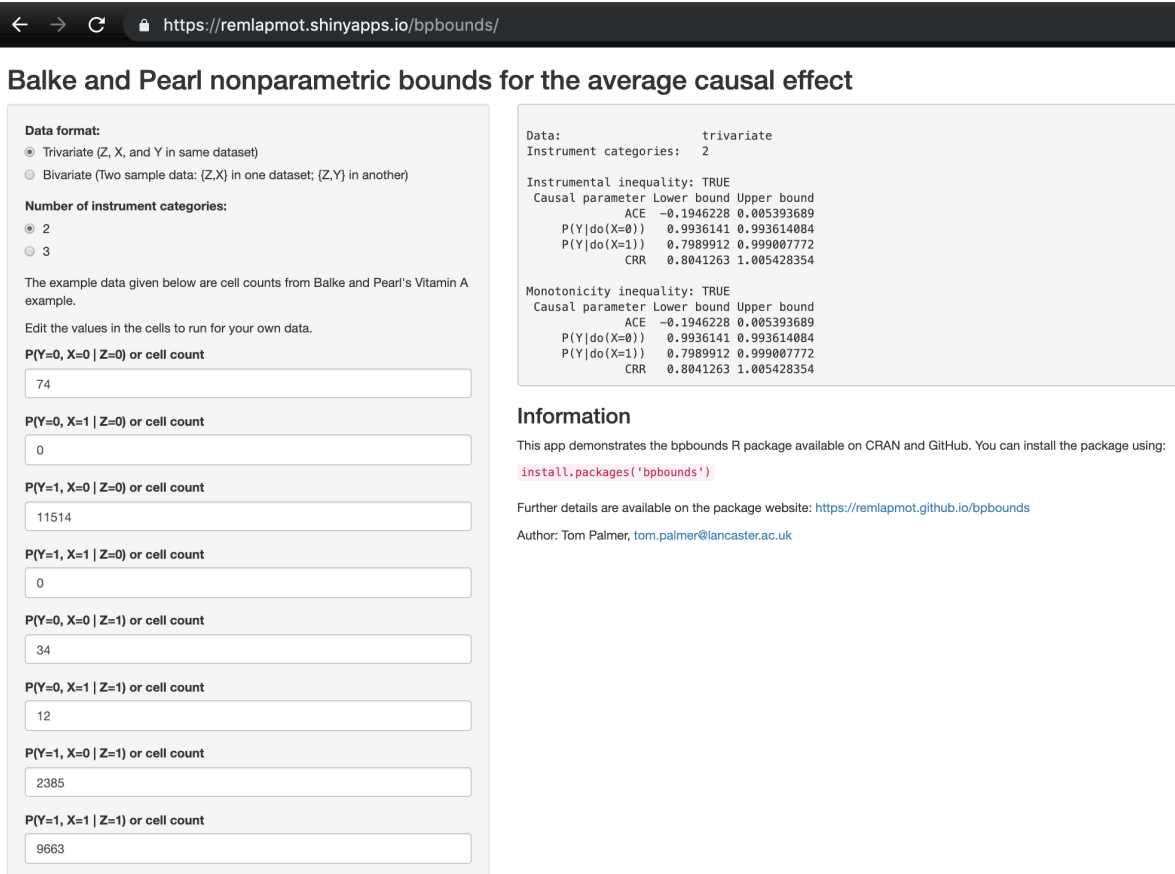


Figure 2: Screenshot of our Shiny app.



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

