

# 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 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:
  - using conditional probabilities calculated from contingency tables;
  - 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

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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>

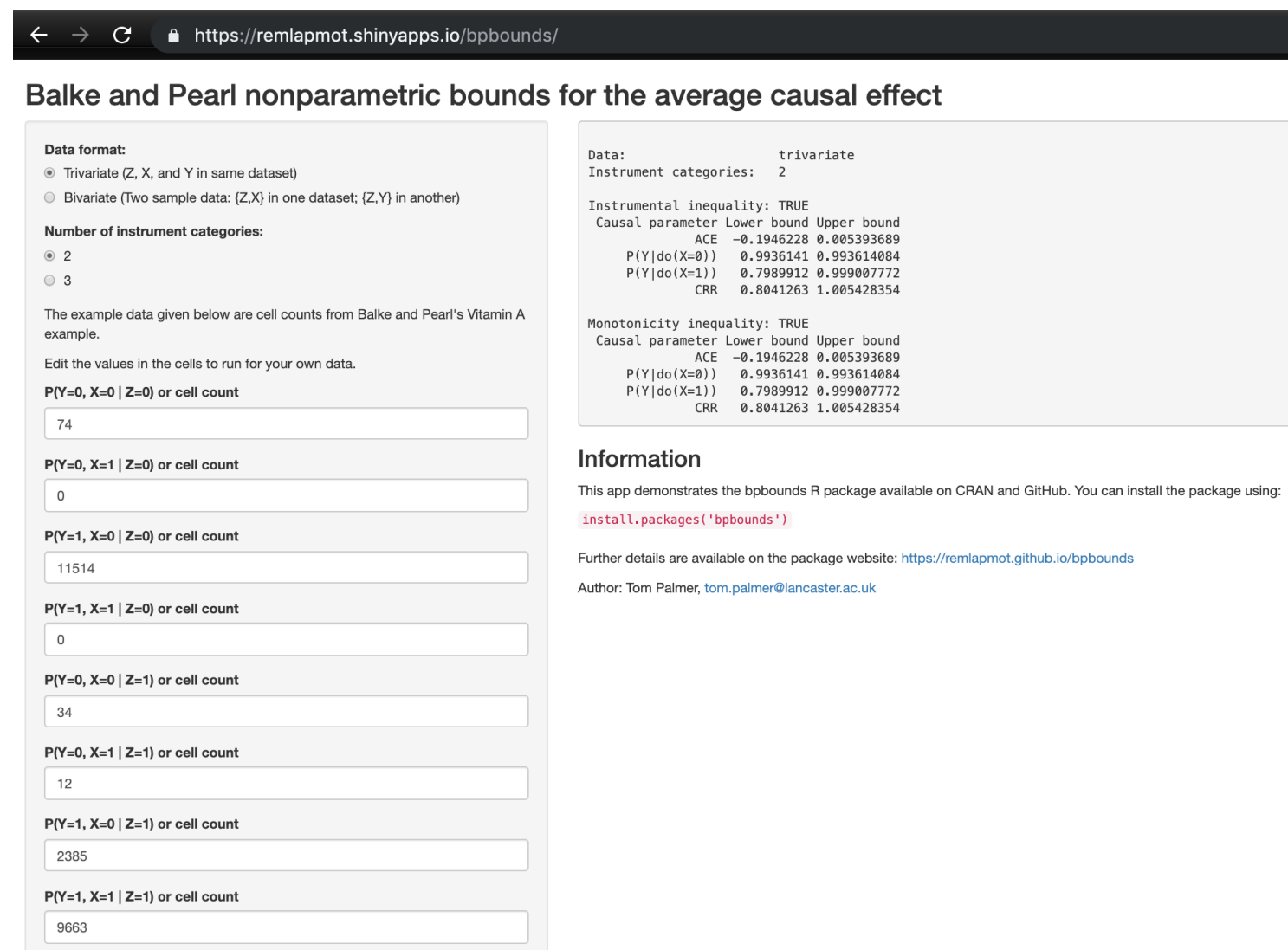


Figure 2: Screenshot of our Shiny app.



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

