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<sup>1, ©</sup>

Roland Ramsahai Vanessa Didelez<sup>2</sup> Nuala Sheehan<sup>3</sup>

<sup>1</sup> Department of Mathematics and Statistics, Lancaster University
 <sup>2</sup> Leibniz BIPS, Bremen, Germany
 <sup>3</sup> 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).
- $\bullet$  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, <u>dim =</u> c(2, 2, 3),
$\underline{\text{dimnames}} = \text{list}(\underline{x} = \mathbf{c}(0, 1)),$
$\underline{y} = c(0, 1),$
$\underline{z} = c(0, 1, 2))$
<pre>bpres3 &lt;- bpbounds(as.table(p3))</pre>
<pre>summary (bpres3)</pre>
##
## ## Data: trivariate
<pre>## ## Data: trivariate ## Instrument categories: 3</pre>
## ## Data: trivariate ## Instrument categories: 3 ##
<pre>## ## Data: trivariate ## Instrument categories: 3 ## ## Instrumental inequality: TRUE</pre>
<pre>## ## Data: trivariate ## Instrument categories: 3 ## ## Instrumental inequality: TRUE ## Causal parameter Lower bound Upper bound</pre>
<pre>## ## Data: trivariate ## Instrument categories: 3 ## ## Instrumental inequality: TRUE ## Causal parameter Lower bound Upper bound ## ACE -0.09 0.74000</pre>
## ## Liver Categories: 3 ## ## 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
##         trivariate           ##         Instrument categories:         3           ##         Instrumental inequality:         TRUE           ##         Causal parameter Lower bound Upper bound         0,74000           ##         P(Y do(X=0))         0.06         0.12000           ##         P(Y do(X=1))         0.03         0.80000
## ## Dats: trivariate ## Instrument categories: 3 ## ## Instrumental inequality: TRUE ## Causal parameter Lower bound Upper bound ## ACE -0.09 0.74000 ## P(X do(X=0)) 0.06 0.12000 ## P(X do(X=1)) 0.03 0.80000 ## CRR 0.25 13.3333

## Monotonicity inequality: FALSE



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

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Figure 2: Screenshot of our Shiny app.



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





