

# Sensitivity Analysis with the $R^2$ -Calculus

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## Sensitivity Analysis is an Optimization Problem

### Problem

- Plethora of methods for sensitivity analysis, but **hardly used in practice**
- Focus on closed-form solutions → simplistic sensitivity models and unintuitive sensitivity parameters

### Our Framework

- $(V_i, U_i)_{i=1}^n \sim \mathbb{P}_{V,U}$ , but only  $(V_i)_{i=1}^n$  is observed
- Objective:  $\beta(\theta, \psi)$ , e.g. causal effect
- $\theta$  are estimable parameters, i.e. only depend on  $\mathbb{P}_V \rightarrow \hat{\theta}$
- $\psi$  are sensitivity parameters, i.e. depend on  $\mathbb{P}_{V,U}$
- Specifying domain knowledge about  $\psi$  as constraints:  
 $g(\theta, \psi) \leq 0 \quad h(\theta, \psi) = 0$
- Solving the **plug-in optimization problem**:  
 $\min_{\psi} / \max_{\psi} \beta(\hat{\theta}, \psi) \quad \text{subject to } g(\hat{\theta}, \psi) \leq 0, h(\hat{\theta}, \psi) = 0$

## $R^2$ -Calculus

Let  $Y$  be a random variable and  $X, W, Z$  be random vectors.  $Y^{\perp X}$  is the residual of  $Y$  after regressing out  $X$ .

### Definitions

- $R^2$ -value:  $R_{Y \sim X}^2 := 1 - \frac{\text{var}(Y^{\perp X})}{\text{var}(Y)}$
- Partial  $R^2$ -value:  $R_{Y \sim X|Z}^2 := \frac{R_{Y \sim X+Z}^2 - R_{Y \sim Z}^2}{1 - R_{Y \sim Z}^2}$
- Partial  $R$ -value:  $R_{Y \sim X|Z} := \text{corr}(Y^{\perp Z}, X^{\perp Z})$
- Partial  $f$ -value:  $f_{Y \sim X|Z} := \frac{R_{Y \sim X|Z}}{\sqrt{1 - R_{Y \sim X|Z}^2}}$

### $R^2$ -Calculus<sup>[2]</sup>

System of algebraic rules for (partial)  $R^2$ - and  $R$ -values, e.g.

(i) Independence: If  $Y \perp\!\!\!\perp X$ , then  $R_{Y \sim X}^2 = 0$

(iv) Recursion of partial correlation:

$$R_{Y \sim X|W} = \frac{R_{Y \sim X} - R_{Y \sim W} R_{X \sim W}}{\sqrt{1 - R_{Y \sim W}^2} \sqrt{1 - R_{X \sim W}^2}}$$

(v) Reduction of partial correlation: If  $Y \perp\!\!\!\perp W$ , then

$$R_{Y \sim X|W} = \frac{R_{Y \sim X}}{\sqrt{1 - R_{X \sim W}^2}}$$

## Sensitivity Analysis in a Linear Model

**Key Idea:** Using  $R$ - and  $R^2$ -values as sensitivity parameters  $\psi$  because they are easy to interpret. [3]

- Causal effect:  $\beta = \beta_{Y \sim D|X,Z,U}$
- Family of  $k$ -class estimands  $\beta_k$ , where  $k \leq 1$ :

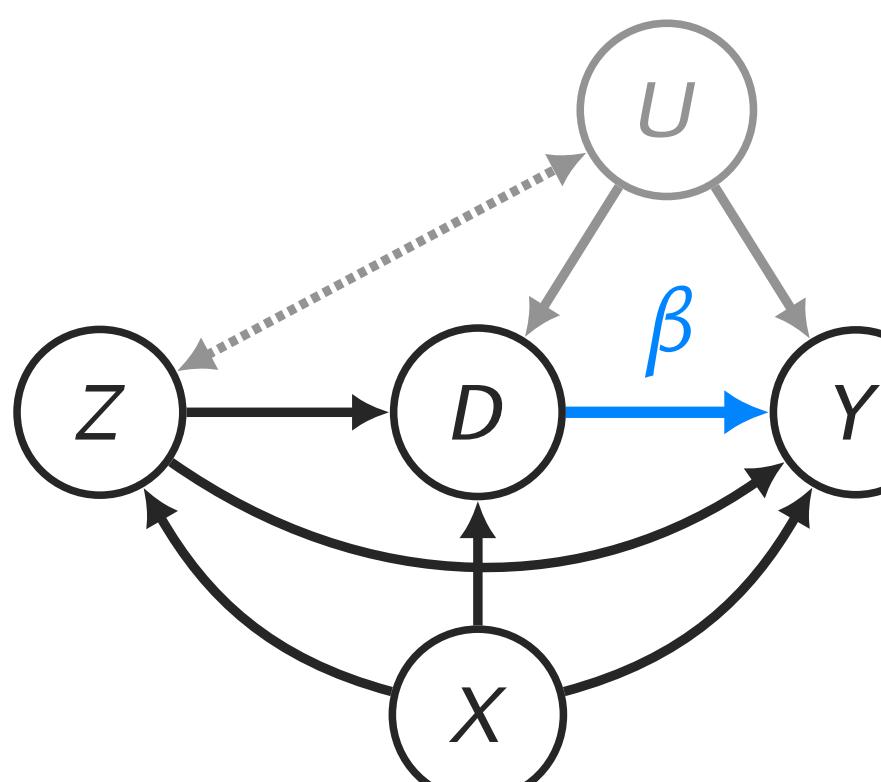
$$\beta_1 = \beta_{TSLS}, \quad \beta_0 = \beta_{Y \sim D|X}, \quad \lim_{k \rightarrow \infty} \beta_k = \beta_{Y \sim D|X,Z}$$

Via the  $R^2$ -calculus, we get:

$$\beta_k - \beta = \left[ \frac{f_{Y \sim Z|X,D} R_{D \sim Z|X}}{1 - k + k R_{D \sim Z|X}^2} + R_{Y \sim U|X,Z,D} f_{D \sim U|X,Z} \right] \frac{\text{sd}(Y^{\perp X,Z,D})}{\text{sd}(D^{\perp X,Z})}$$

Choose the sensitivity parameters:

$$\psi = (R_{Y \sim U|X,Z,D}, R_{D \sim U|X,Z})$$

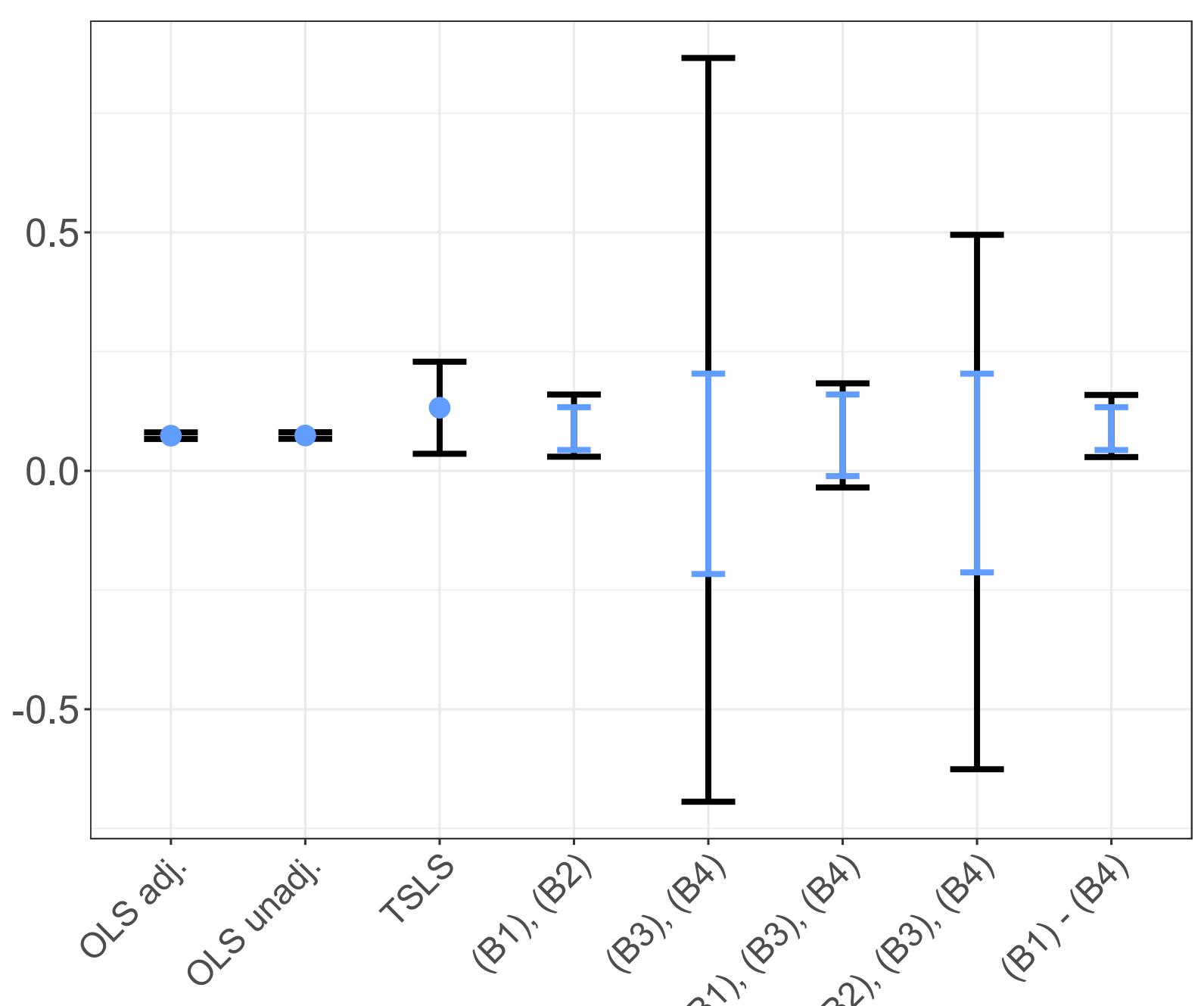


## Practical Application

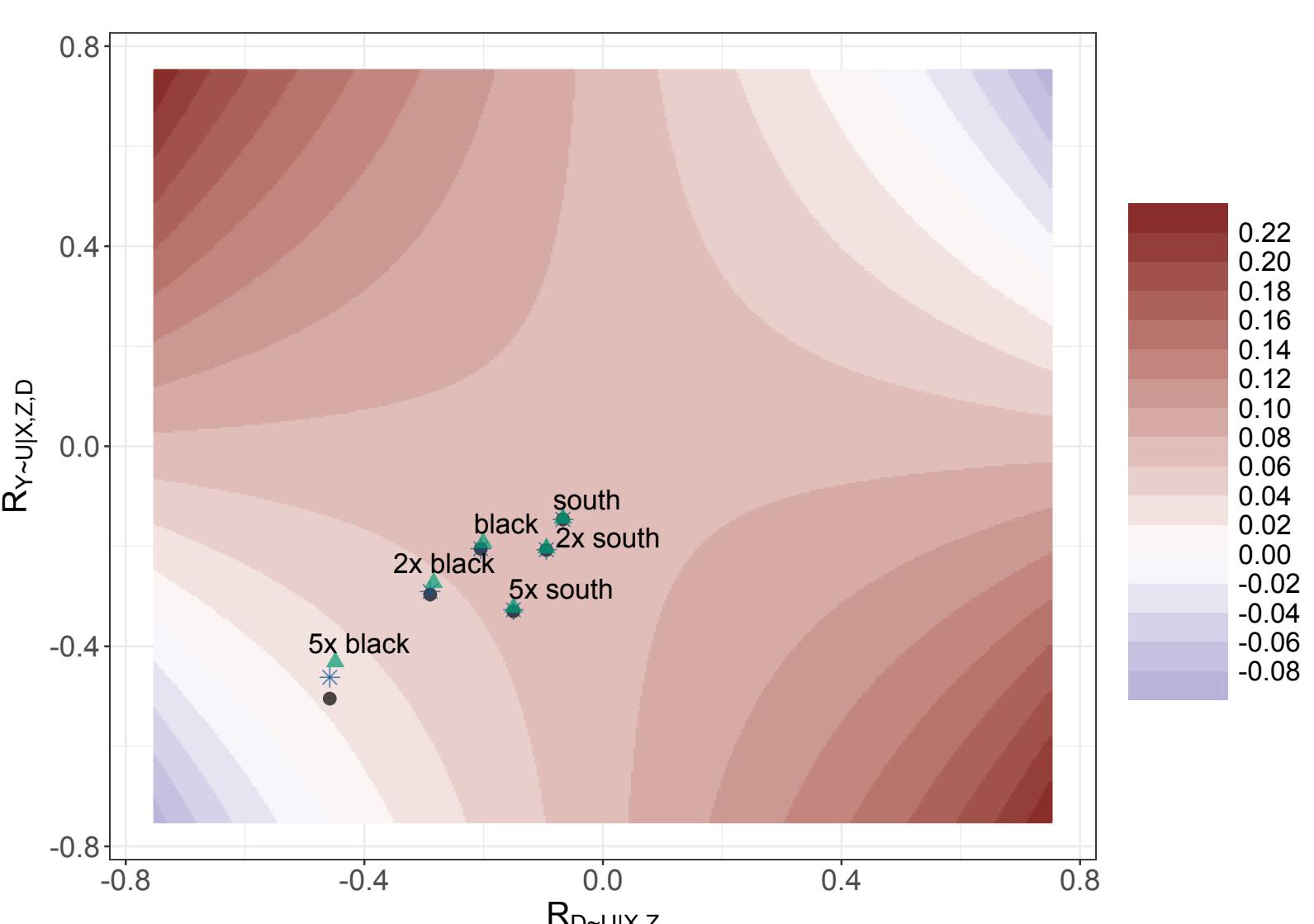
- National Longitudinal Survey of Young Men [4]
- Causal effect  $\beta$  of education  $D$  on salary  $Y$
- Potential instrument  $Z$ : growing up close to a college
- Baseline covariates  $X$ :  $\tilde{X}$  indicator for being black,  $\check{X}$  remaining covariates
- Unmeasured confounder  $U$ : motivation

Sensitivity analysis with comparative bounds:

- (B1)  $R_{D \sim U|\tilde{X},Z}^2 \leq 4 R_{D \sim \tilde{X}|\tilde{X},Z}^2$  (B2)  $R_{Y \sim U|\tilde{X},Z,D}^2 \leq 5 R_{Y \sim \tilde{X}|\tilde{X},Z,D}^2$   
(B3)  $R_{Z \sim U|\tilde{X}}^2 \leq 0.5 R_{Z \sim \tilde{X}|\tilde{X}}^2$  (B4)  $R_{Y \sim Z|X,U,D}^2 \leq 0.1 R_{Y \sim \tilde{X}|Z,U,D}^2$



Range of estimates (blue)  
95% confidence intervals (black)



Strength of  $U$  in comparison with observed covariates

## References

- Tobias Freidling and Qingyuan Zhao. Sensitivity analysis with the  $R^2$ -calculus. arXiv 2301.00040, 2023.
- T. W. Anderson. An introduction to multivariate statistical analysis. Wiley Publications in Mathematical Statistics, New York; London, 1st edition, 1958.
- Carlos Cinelli and Chad Hazlett. Making sense of sensitivity: extending omitted variable bias. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 82(1):39–67, 2020.
- David Card. Using Geographic Variation in College Proximity to Estimate the Return to Schooling. Technical Report w4483, National Bureau of Economic Research, 1993.

