An Omitted Variable Bias Framework for Sensitivity Analysis of Instrumental Variables

Carlos Cinelli (UCLA) and Chad Hazlett (UCLA)

Motivating Example:
Estimating the Returns to Schooling

Returns to schooling — OLS suffers from OVB

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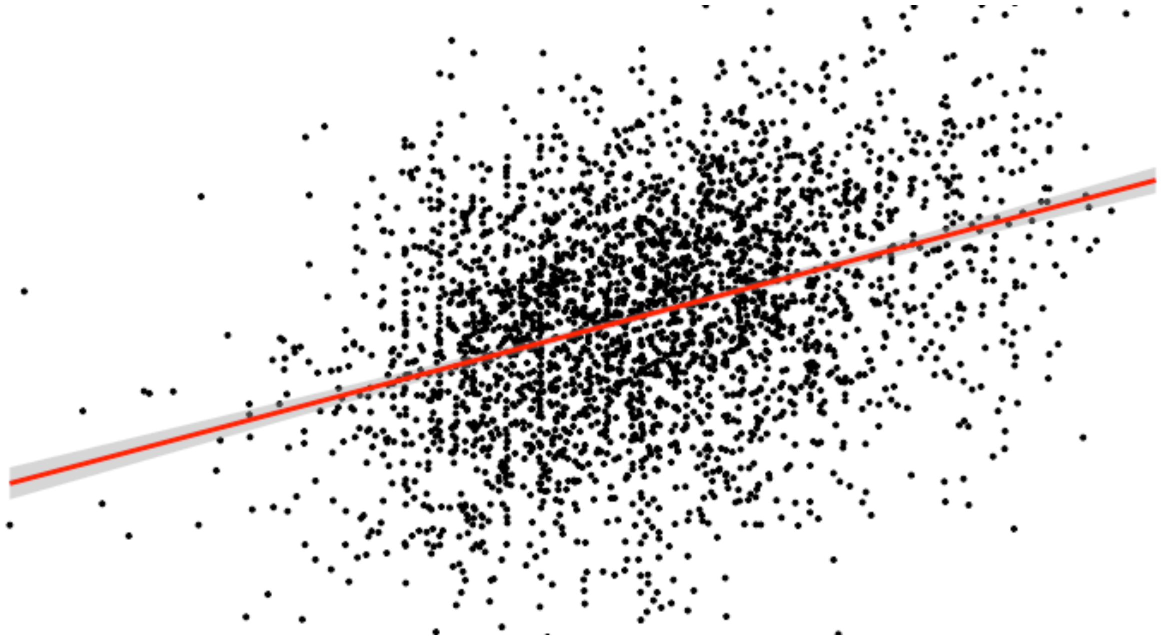

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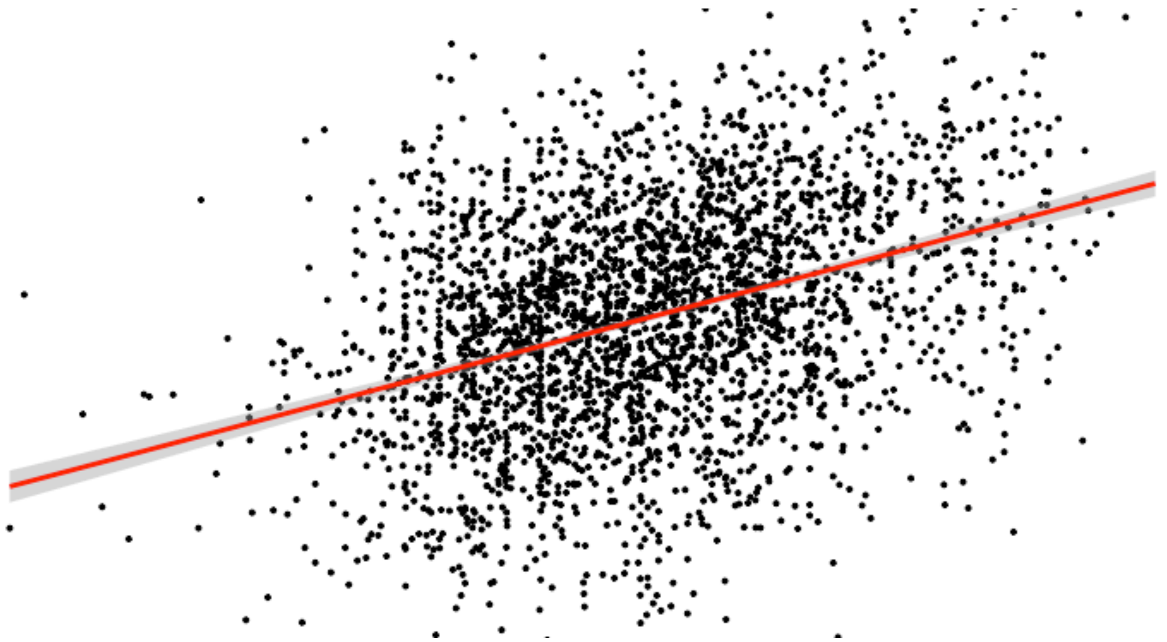

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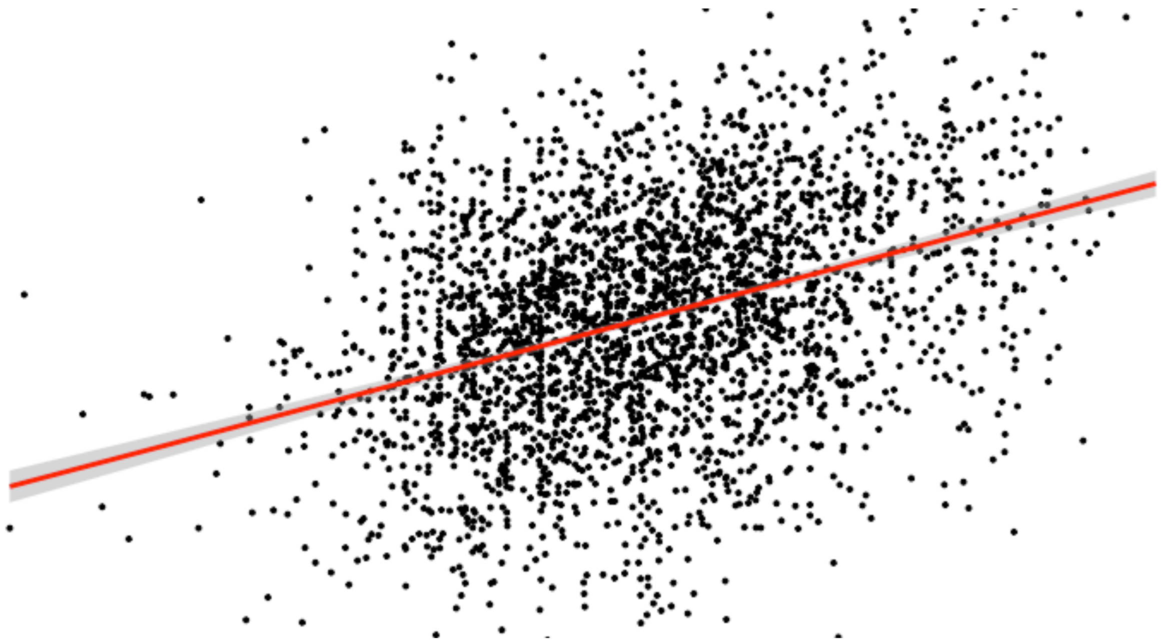

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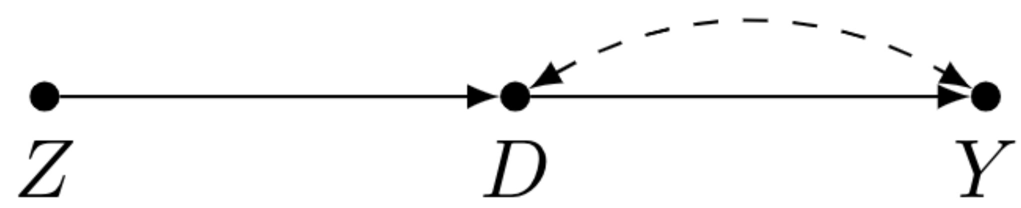
Our restricted OLS estimate is not causal, and may suffer from what is known as ***"omitted variable bias" (OVB). What can we do now?***

Returns to schooling — IV comes to the rescue (?)

If we can find a variable *Z* that (i) changes the incentives to schooling (*D*); and (ii) is "otherwise" unrelated to earnings (*Y*), then we can obtain a valid estimate* of the causal effect of schooling on earings, *even without measuring unobserved confounders U.*



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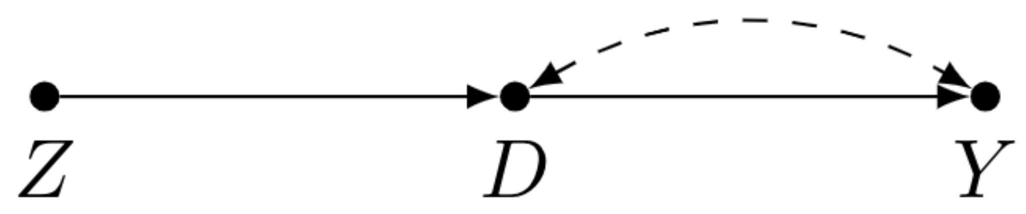

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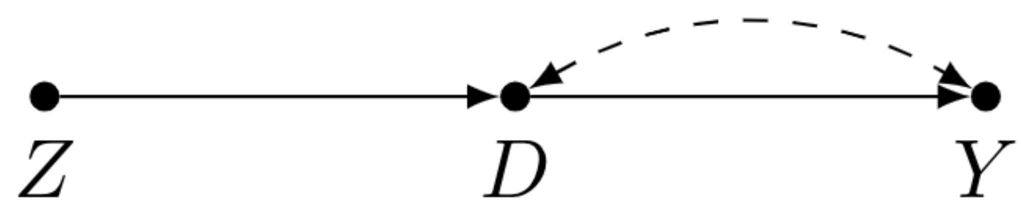

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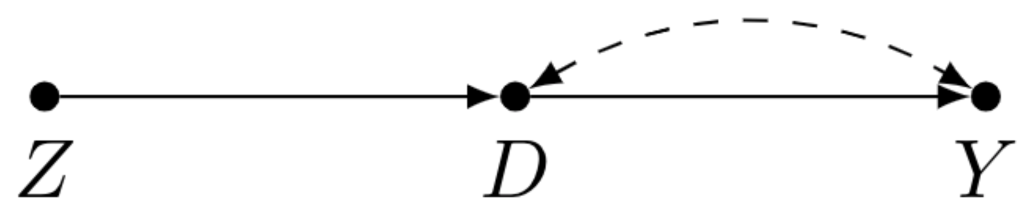

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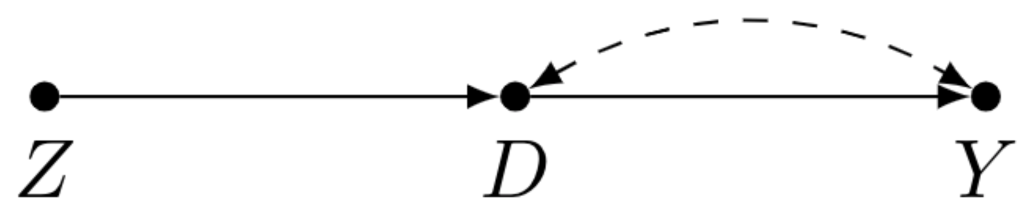

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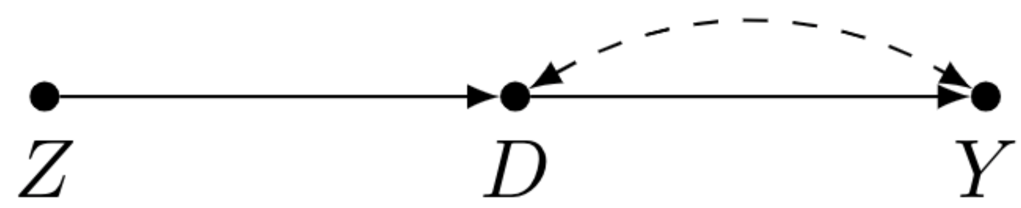

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But proximity is not randomized… couldn't we have the same problem as with OLS?

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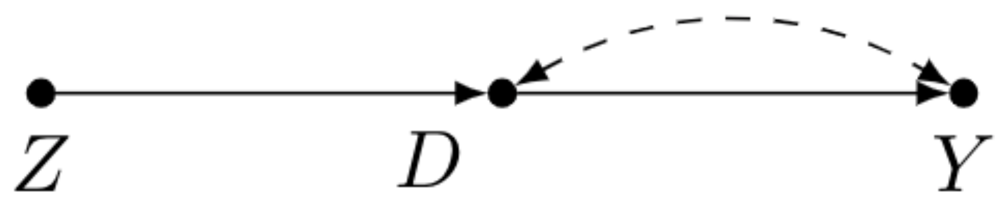
Returns to schooling — IV can also suffer from OVB

In general there are two main threats for the validity of an IV estimate:



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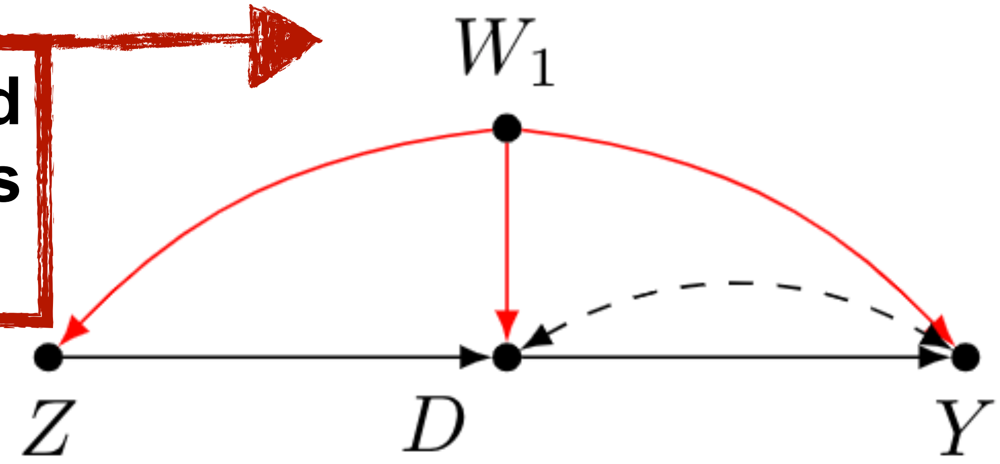

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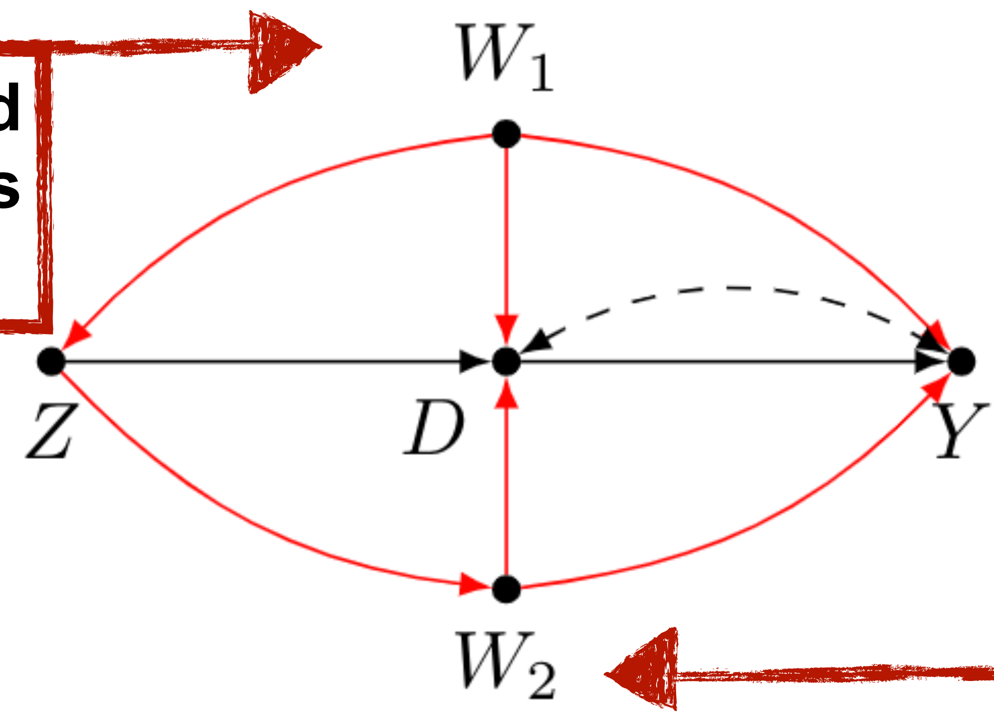

“Side-effects” of Z (“exclusion restriction” is violated)

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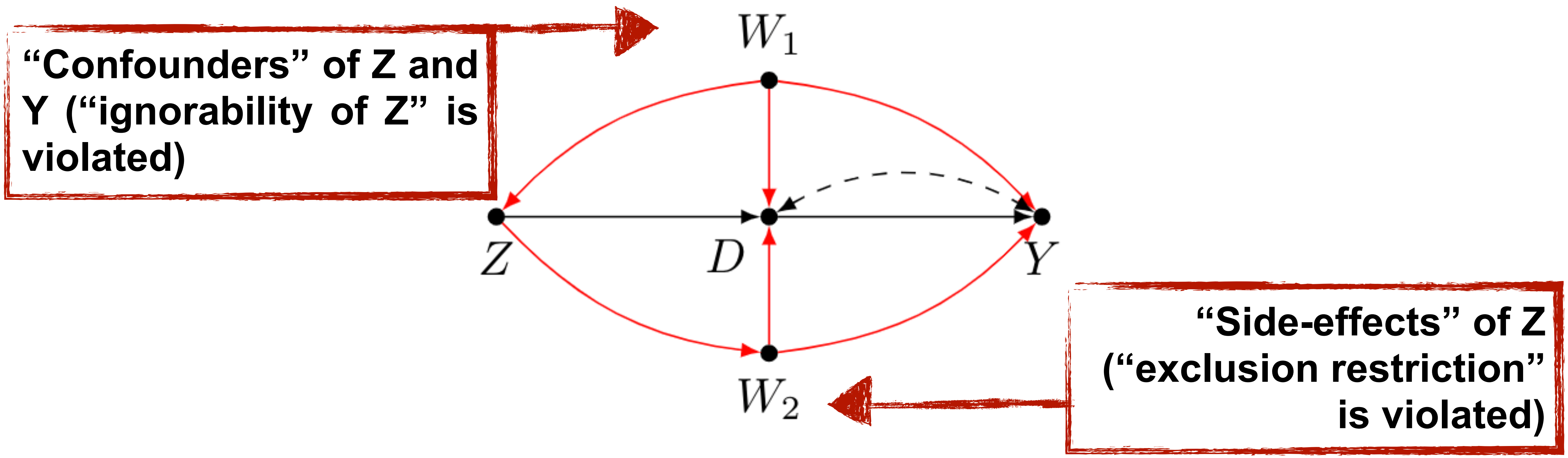

And this is indeed the case in Card’s example. For instance, family wealth, or simply better regional indicators are likely confounders of proximity, but we did not measure them.

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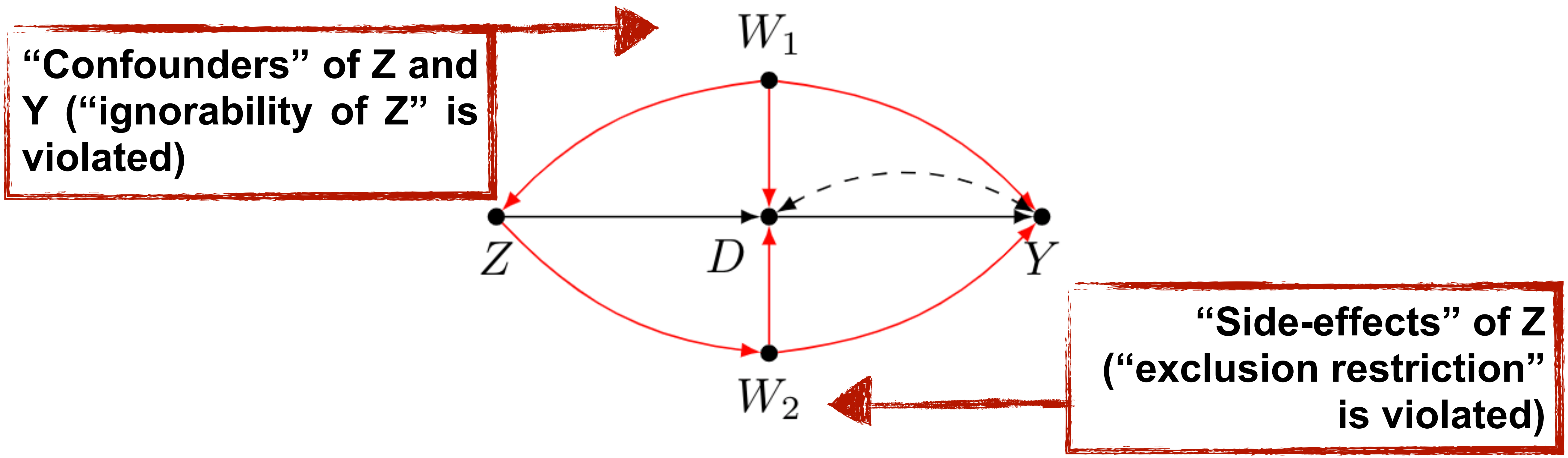

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Although we proposed IV as a solution to the OVB problem, it may itself suffer from OVB! How much can we trust the 13.2% estimate?

The two main approaches to IV estimation: just different flavors of OLS

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$$\hat{\tau}_{\text{ILS,res}} := \frac{\text{Effect of Z on Y (RF)}}{\text{Effect of Z on D (FS)}} = \frac{\hat{\lambda}_{\text{res}}}{\hat{\theta}_{\text{res}}} \approx \frac{0.042}{0.319} \approx 13.2\,\%$$

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(Identical to Fieller's (1954) proposal for the confidence interval of a ratio.)

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This approach has correct test size regardless of instrument strength.

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At their core, IV estimates are OLS estimates.
So we can leverage all sensitivity tools for OLS for the sensitivity of IV.

An Omitted Variable Bias Framework for Instrumental Variables

OVB for IV — what can we learn from RF and FS?

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Point estimate: this formally holds for ***all estimators*** discussed here.
Confidence intervals: this formally holds for the ***AR/Fieller approach.***

(significance testing using ILS/2SLS can lead to logically incoherent conclusions)

OVB for IV — crash course on OVB for OLS

(using the reduced form as the example)

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3. Formal bounds on the strength of W if it were as strong as observed covariates

- Leverage claims of relative importance of variables.

OVB for IV — Anderson-Rubin

For a choice of τ_0 create the “putative potential outcome” $Y_{\tau_0} := Y - \tau_0 D$ and run the AR regression:

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- With this, we can get all usual OLS sensitivity results for IV estimates, such defining (extreme) robustness values, contour plots, etc.

Back to schooling

Minimal sensitivity reporting — zero effect (RF)

Outcome: *Earnings* (log)

Instrument	Estimate	S.E.	t-value	$R^2_{Y\sim Z\|\mathbf{X}}$	$\text{XRV}_{q^*,\alpha}$	$\text{RV}_{q^*,\alpha}$
Proximity	0.042	0.018	2.33	0.18%	0.05%	0.67%

Bound (1x smsa): $R^2_{Y\sim W|Z,\mathbf{X}} = 2\%$, $R^2_{Z\sim W|\mathbf{X}} = 0.6\%$, $t^{\dagger}_{\alpha,\text{df}-1,\boldsymbol{R}^2} = 2.55$

Note: df $= 2994$, $q^* = 1$, $\alpha = 0.05$

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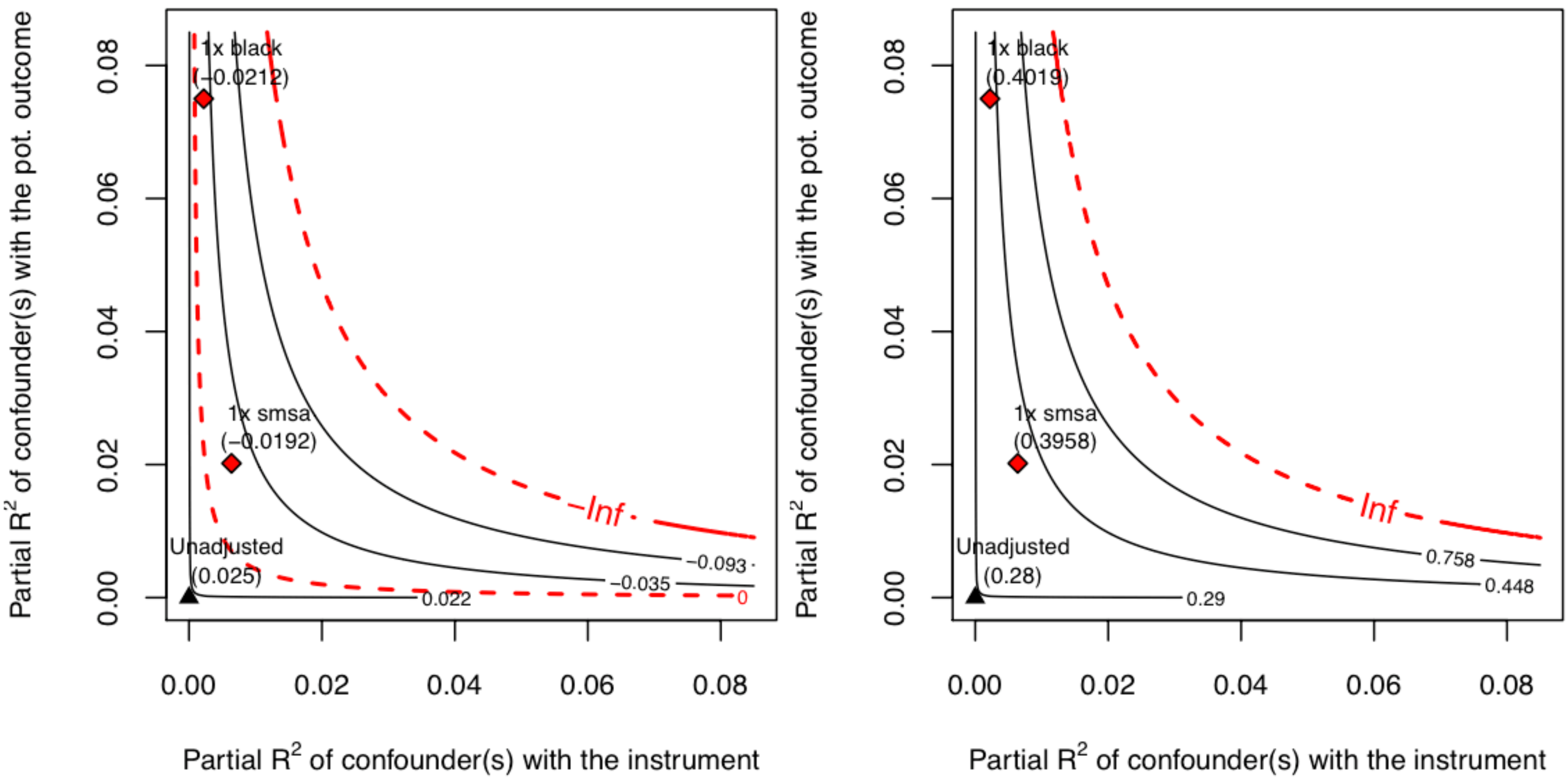
Sensitivity contours — AR lower and upper limits



(a) Sensitivity contours: lower limit (b) Sensitivity contours: upper limit

Figure: Sensitivity contour plots for the lower (a) and upper (b) limits of the 95% confidence interval for the IV estimate.

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- Sensitivity of the reduced form, first stage or a specific null hypothesis using the Anderson-Rubin regression can already be easily performed with sensemakr. Software for the full-fledged IV sensitivity will be available soon (for R and Stata).

Learn more!

- ***Watch the presentation on youtube*** (link: https://tinyurl.com/ovb4iv)

- ***An Omitted Variable Bias Framework for Sensitivity Analysis of Instrumental Variables (preliminary draft)*** (link: https://tinyurl.com/ovb4iv-draft)

- ***Making Sense of Sensitivity: Extending Omitted Variable Bias*** (link: https://tinyurl.com/jrssb)

- ***sensemakr: Sensitivity Analysis Tools for OLS in R and Stata*** (link: https://tinyurl.com/jss-sensemakr)

THANK YOU!