

# What to Do with Unclassifiable Outcomes in International Relations Data

Brenton Kenkel

Department of Political Science, University of Rochester

## Motivation

IR datasets often have observations where the dependent variable cannot be coded easily:

- ▶ Continued disputes and joiners in COW
- ▶ Measures disagree (MID initiation: Side A or Revisionist?)
- ▶ Values just above/below arbitrary thresholds

From a statistical standpoint, these constitute nonrandom missing data or measurement error, so deleting them from the dataset will cause bias.

I develop a new method to check the robustness of logistic regression results when some outcomes are unclassifiable or unobserved, without introducing bias or making implausible assumptions.

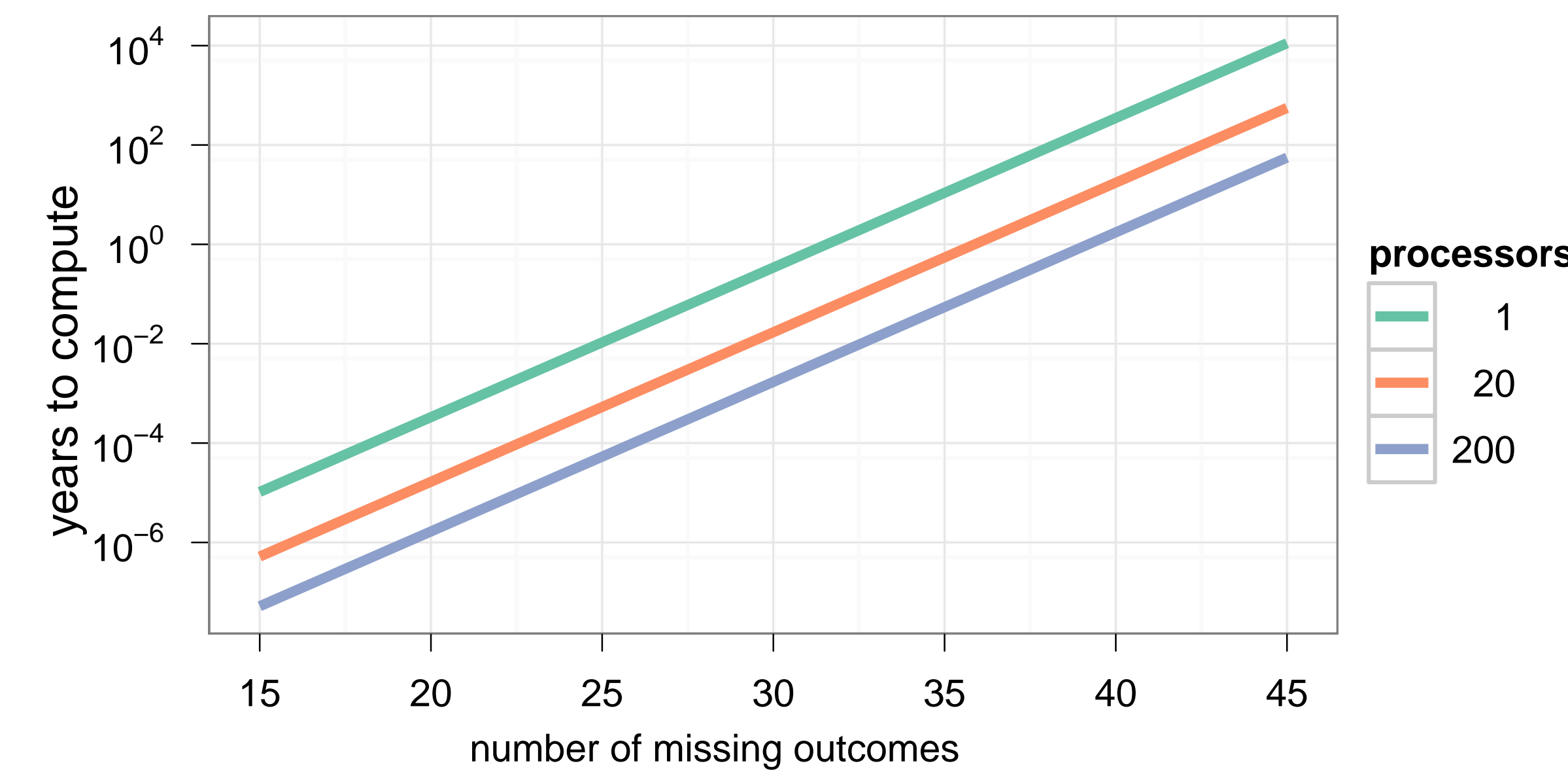
## Methodology

**Ideal Procedure:** Run logistic regression on all possibilities, check for no substantive difference in results.

observed	controls		possibilities				controls	
$Y$	$X_1$	$X_2$	$Y^{(1)}$	$Y^{(2)}$	$Y^{(3)}$	$Y^{(4)}$	$X_1$	$X_2$
?	8	5	0	0	1	1	8	5
?	2	4	0	1	0	1	2	4
0	7	2	0	0	0	0	7	2
1	1	10	1	1	1	1	1	10
0	3	5	0	0	0	0	3	5
1	2	3	1	1	1	1	2	3

fill in the missing values

**The Problem:** Computationally infeasible.



### My Approach:

- ▶ Treat unclassifiable outcomes as nonignorable missing data
- ▶ Use moment conditions to approximate the results of the “ideal” procedure much more quickly (similar to Manski & Tamer 2002)

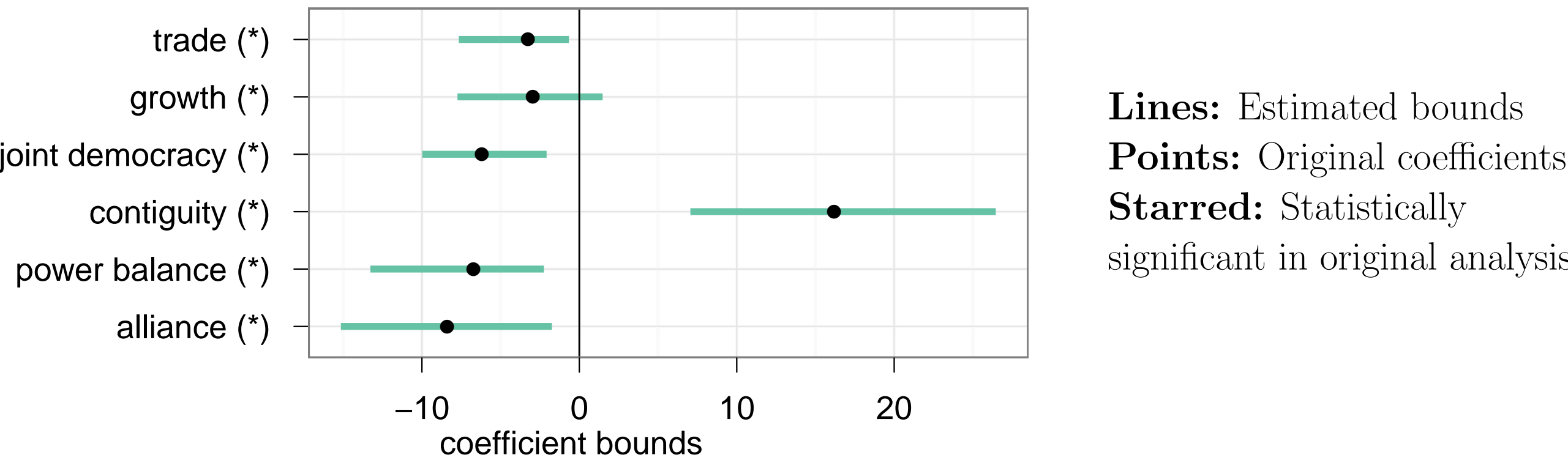
## Application 1: Oneal and Russett (1997) on Liberal Peace

Sample: Politically relevant dyads ( $N = 20,990$ )

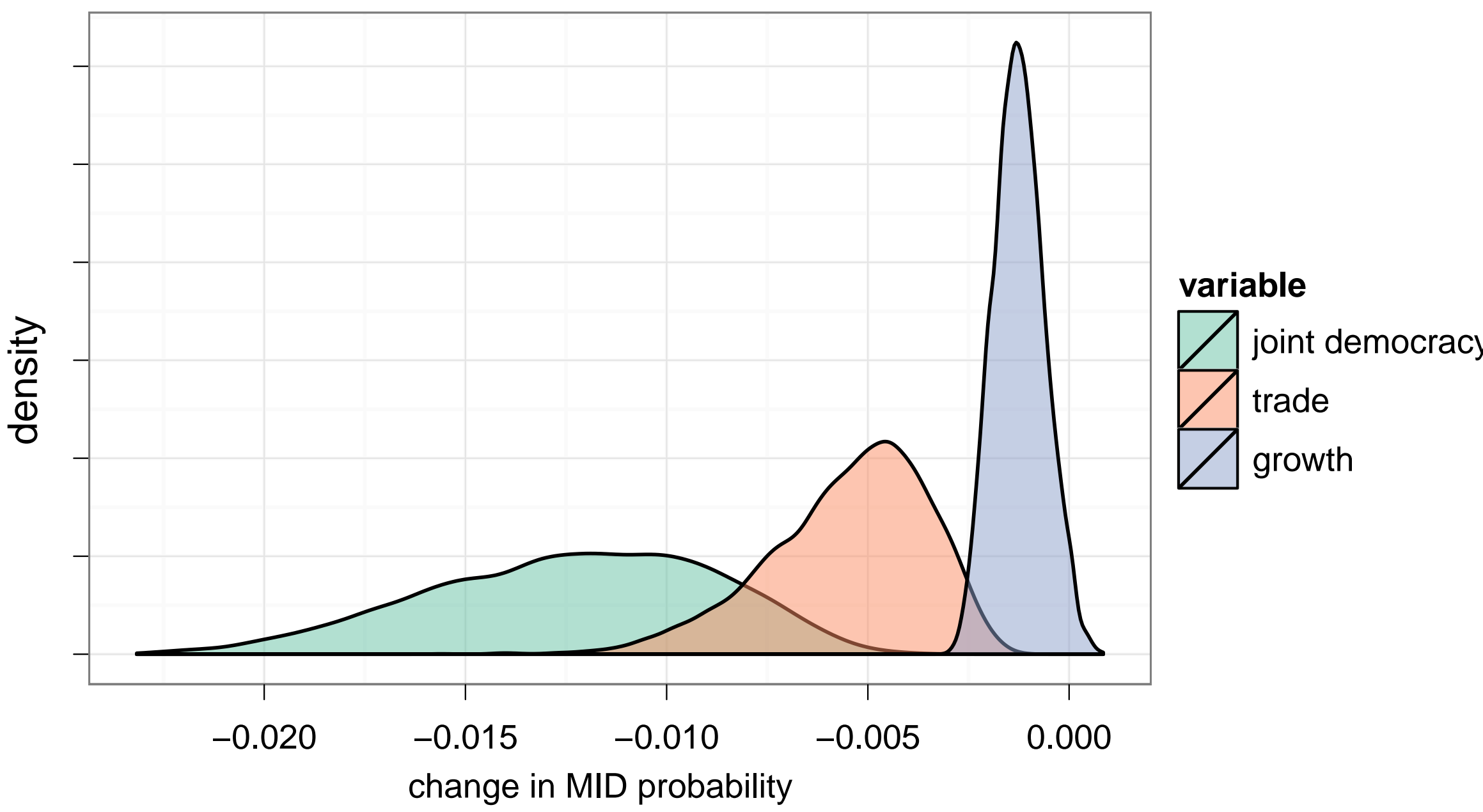
Outcome: Militarized dispute onset (405 cases)

Unclassifiable values: Continued disputes (542 cases)

### Main Results



### Substantive Effects



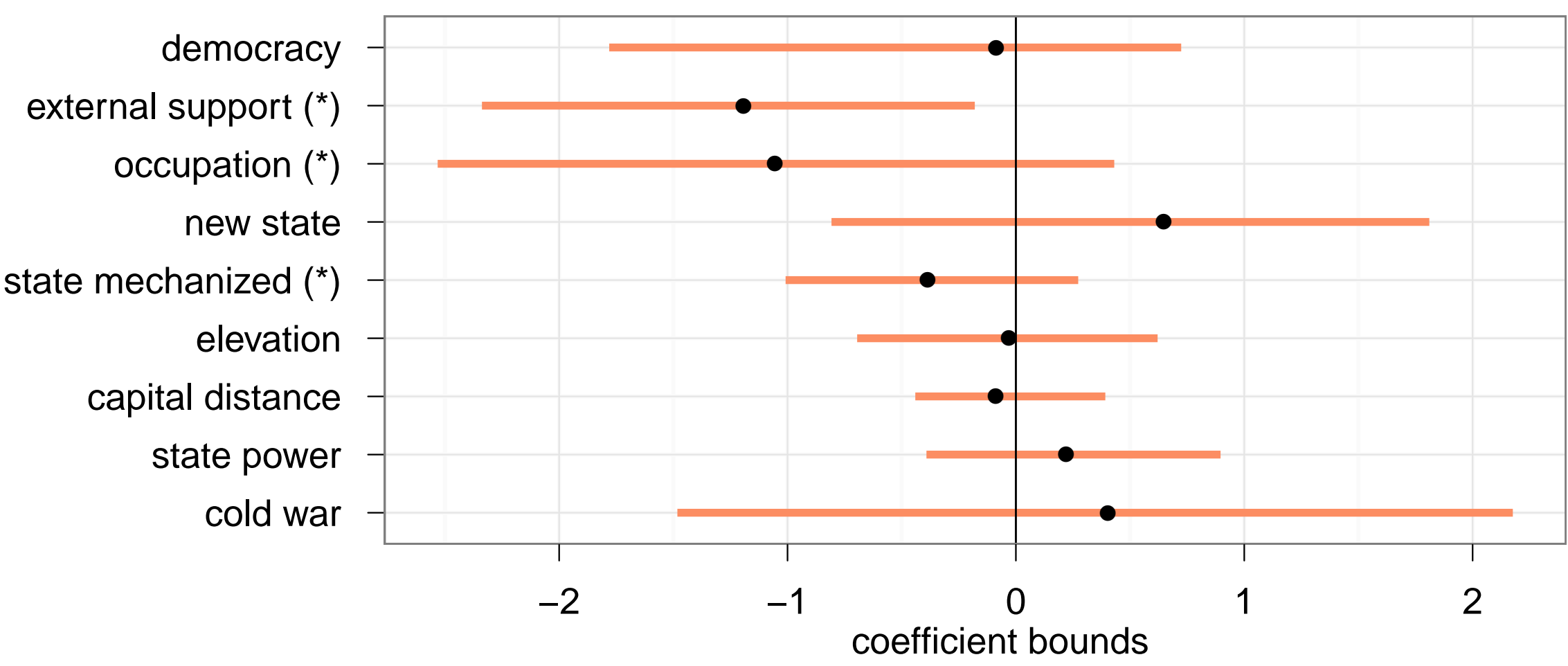
## Application 2: Lyall (2010) on Counterinsurgencies

Sample: Counterinsurgency efforts ( $N = 286$ )

Outcome: Victory against insurgency (153 cases)

Unclassifiable values: “Difficult to code” draw (39 cases)

### Main Results



## Interpreting the Results

The bounds contain the set of coefficients that could be obtained as a *point estimate* under some assumption about the missing values—no population inference is implied.

If the bounds contain 0, the sample definitely does not provide evidence in favor of a directional hypothesis. However, failure to contain 0 only establishes that the sign of the sample estimate is robust to missingness/measurement error.

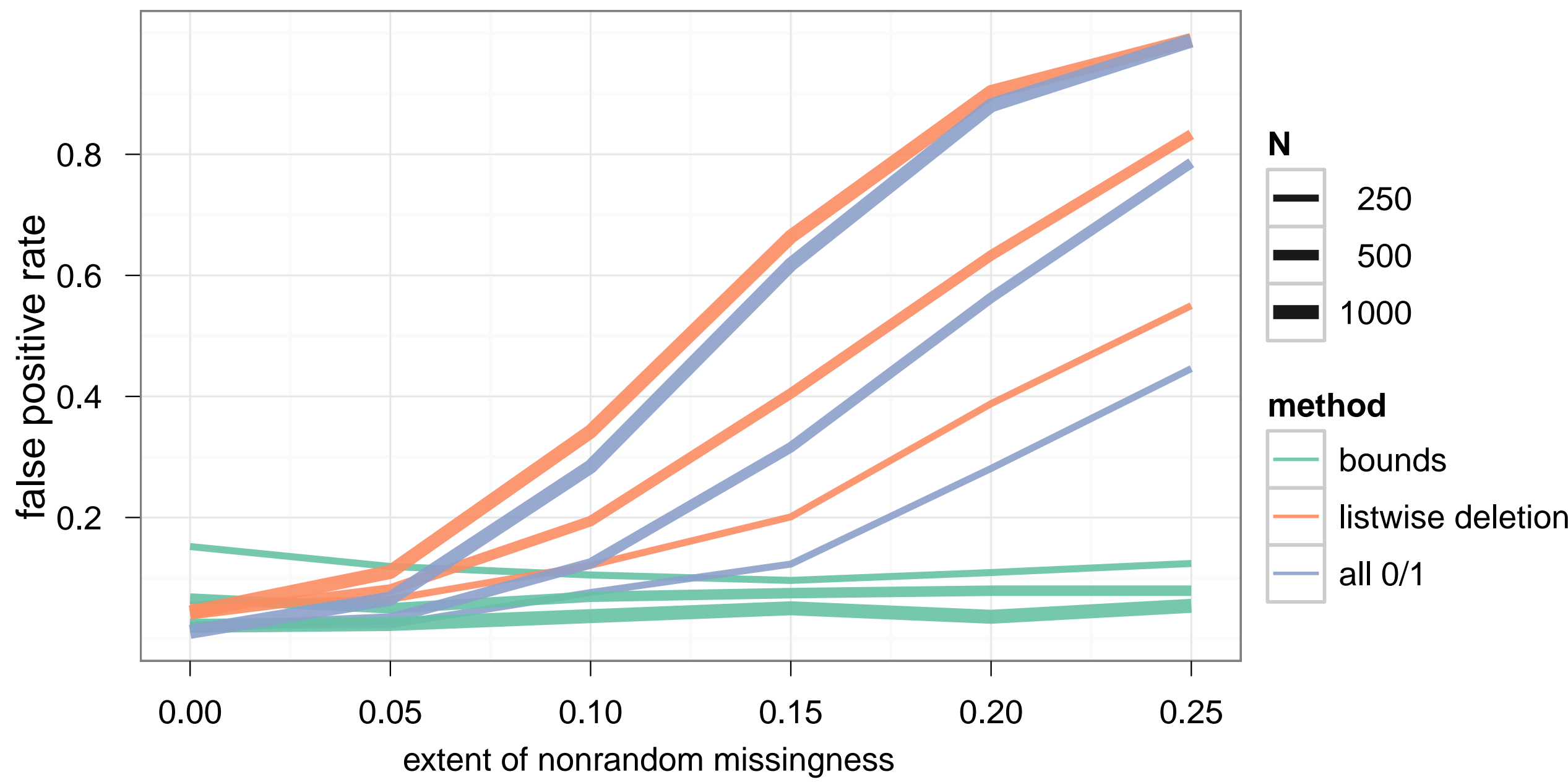
## Monte Carlo Simulation

Comparison of the new method to common robustness checks in IR:

- ▶ Listwise deletion of unclassifiable outcomes
- ▶ Setting all to 0 or all to 1

Suppose the value of  $Y$  does not depend on  $X$ , but the probability of missingness depends on  $Y$  and  $X$  (hence is nonrandom). How well does each method perform at avoiding false positives?

### Results



As  $N$  increases, the bounding method performs better (fewer false positives), while the other two get worse.

## References

- Jason Lyall. 2010. “Do Democracies Make Inferior Counterinsurgents? Reassessing Democracy’s Impact on War Outcomes and Duration.” *International Organization*, 64(1): 167–192.
- Charles F. Manski and Elie Tamer. 2002. “Inference on Regressions with Interval Data on a Regressor or Outcome.” *Econometrica* 70(2): 519–546.
- John R. Oneal and Bruce M. Russett. 1997. “The Classical Liberals Were Right: Democracy, Interdependence, and Conflict, 1950–1985.” *International Studies Quarterly* 41(2): 267–293.