

Assessing Omitted Variable Bias when the Controls are Endogenous*

Paul Diegert[†] Matthew A. Masten[‡] Alexandre Poirier[§]

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Abstract

Omitted variables are one of the most important threats to the identification of causal effects. Several widely used methods assess the impact of omitted variables on empirical conclusions by comparing measures of selection on observables with measures of selection on unobservables. The recent literature has discussed various limitations of these existing methods, however. This includes a companion paper of ours which explains issues that arise when the omitted variables are endogenous, meaning that they are correlated with the included controls. In the present paper, we develop a new approach to sensitivity analysis that avoids those limitations, while still allowing researchers to calibrate sensitivity parameters by comparing the magnitude of selection on observables with the magnitude of selection on unobservables as in previous methods. We illustrate our results in an empirical study of the effect of historical American frontier life on modern cultural beliefs. Finally, we implement these methods in the companion Stata module `reg sensitivity` for easy use in practice.

JEL classification: C18; C21; C51

Keywords: Treatment Effects, Sensitivity Analysis, Unconfoundedness

*This paper is a revised, shorter version of our now-superseded previous working paper titled “Assessing Omitted Variable Bias when the Controls are Endogenous” (Diegert, Masten, and Poirier 2023, arXiv:2206.02303v4), without the design-based framework of Section 3. The design-based framework and associated results can now be found in our companion paper “An Axiomatic Approach to Comparing Sensitivity Parameters” (Diegert, Masten, and Poirier 2025). We thank audiences at Northwestern, Duke, the SEA 2021 conference, Oxford, Brown, Texas A&M, the joint Bonn-Mannheim seminar, Jinan University, the 2022 Interactions Conference at The University of Wisconsin-Madison, University of Virginia, UC Irvine, UC San Diego, UCLA, Ohio State, Yale, Penn, the 2023 AEA winter meeting, Johns Hopkins, George Washington University, Stanford, UC Santa Cruz, Western Ontario, UIUC, Michigan State, Rochester, the Federal Reserve Bank of Cleveland, the 2023 American Causal Inference Conference, and the joint CREST-PSE seminar. We thank audiences at those seminars and conferences, as well as Joe Altonji, Isaiah Andrews, Peter Hull, Evan Rose, and Jon Roth for helpful conversations and comments. We thank Hongchang Guo and Muyang Ren for excellent research assistance. Masten thanks the National Science Foundation for research support under Grant 1943138.

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Notational differences:

- d is X in DMP
- X is W_1
- W is W_2
- (α, β, γ) is $(\beta, \gamma_1, \gamma_2)$
- ν is a linear projection (e.g. $Y^{\perp X, W}$)
- y is capitalized in DMP

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- α_{long} = true treatment effect; α_{med} = the one we can feasibly estimate

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- \bar{c} bounds how much X (jointly) can predict W ($\bar{c} = 0$ in all prior literature)

$$R_{W,X} \leq \bar{c}$$

(assumes W is a single omitted variable)

Formula for \bar{r}_d^{bp} is a function of $R_{Y \sim d \cdot X}^2$ and partial R^2 terms:

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 - Main equation becomes

$$\dot{y} = \alpha \dot{d} + \dot{X}\beta + \underbrace{\dot{W}\gamma + \dot{\nu}}_{\dot{\epsilon}} \quad (3)$$

where $\dot{y} = y_{it} - \bar{y}_i$, etc. Requires time-varying treatment!