Supplementary Appendix for Blair, Chou, and Imai. "List Experiments with Measurement Error"

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April 14, 2019

In this supplementary appendix, we present additional simulation results that build on the results shown in Section 3.

Figure A.1 illustrates the properties of the ML and novel measurement error models introduced in this paper when we increase the underlying prevalence of the sensitive trait. The corresponding figure in the paper is Figure 2. Increasing the underlying prevalence tends to improve the performance of all the models, although the ML and constrained ML models remain positively biased. The constrained models improve inference for the prevalence of the sensitive trait regardless of the measurement error mechanism. However, it is not possible to improve inference for the coefficients under measurement error without assuming the error mechanism and using the corresponding model.

Figure A.2 replicates Figure 1 with the number of control items increased from $J = 3$ to 4. The substantive conclusions remain the same.

Figure A.3 replicates Figure 2 with the number of control items increased from $J = 3$ to 4. This somewhat increases the bias of the estimated slope coefficients. However, the substantive conclusions are unchanged. Specifically, the constrained models help the proportion but not the covariates, while the measurement error models are needed to improve inference for the covariates. Again, the standard MLE is more robust to uniform measurement error than to top-biased error.

Figure A.4 replicates Figure A.1 with the number of control items increased from $J = 3$ to 4. The substantive conclusions remain the same.[1]

References

Ahlquist, John S. 2017. "List Experiment Design, Non-Strategic Respondent Error, and Item Count Technique Estimators." *Political Analysis*.

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[1]Due to the relatively small number of simulations, bias in the top-biased model under top-biased error does not appear to converge toward zero and bias in the uniform model under uniform error does not appear to converge toward zero. In a larger simulation with 5000 simulations, this simulation error disappears and bias for each model under their assumed data-generating processes converges toward zero.

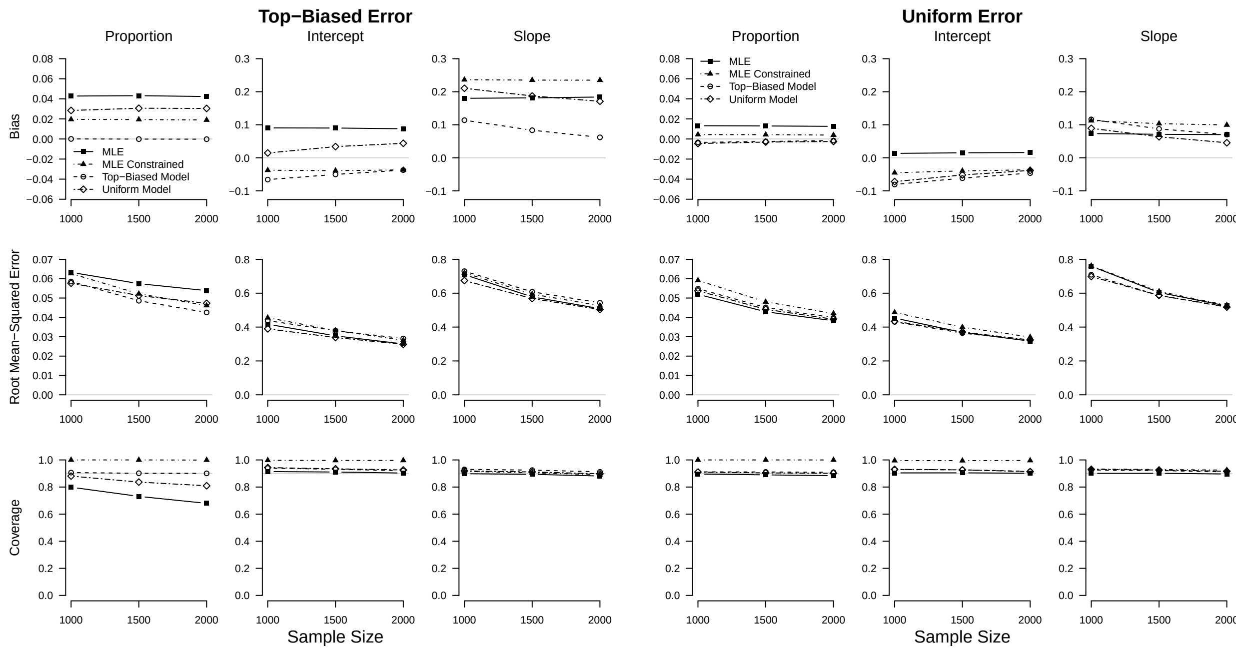

Figure A.1: Robustness of the Constrained and Measurement Error Maximum Likelihood Estimators in the Presence of Response Errors when the Propensity of Sensitive Trait is High. We consider four estimators of the prevalence of the sensitive trait and slope and intercept regression coefficients: the standard maximum likelihood (ML) estimator (solid square with solid line), the constrained ML estimator (solid triangle with dot-dash line), the ML estimators adjusting for top-biased response error (open circle with dashed lines) and uniform response errors (open diamond with dot-long-dash line). The result shows that both the constrained MLE estimator and the models adjusting for response error are an improvement over the performance of the MLE estimator.

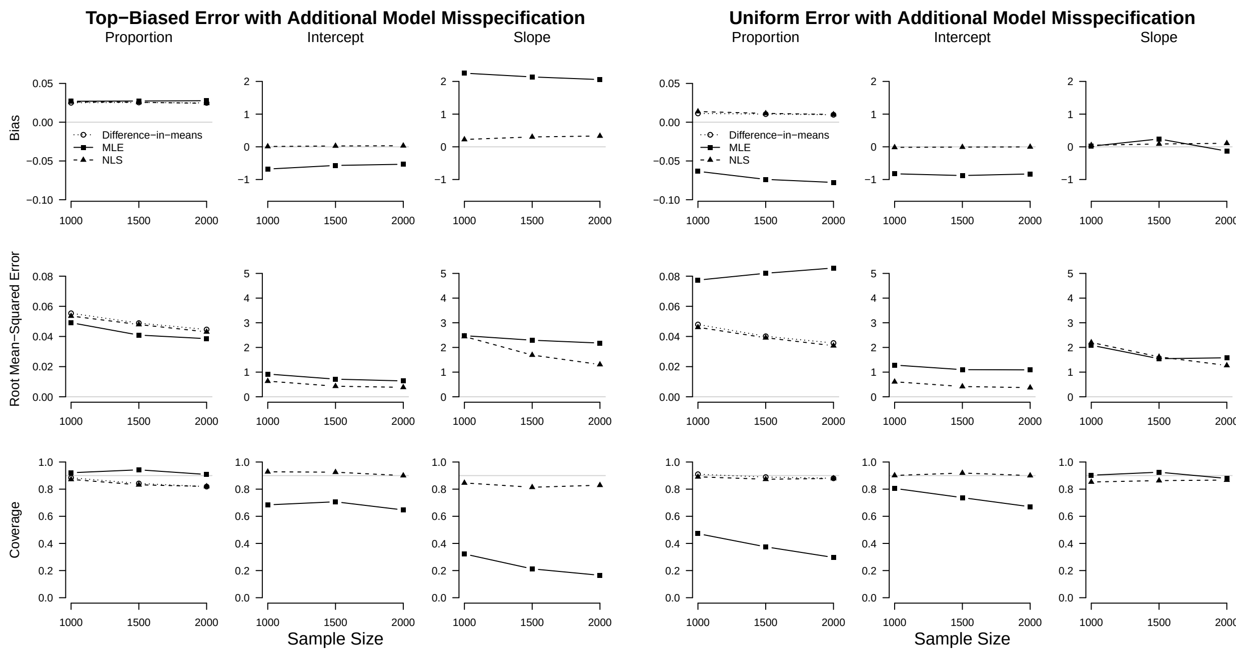

Figure A.2: Robustness of the Nonlinear Least Squares Regression Estimator in the Presence of Several Model Misspecifications Considered in Ahlquist (2017) for $J = 4$. We consider the three estimators of the prevalence of the sensitive trait: the difference-in-means estimator (open circle with dotted line), the maximum likelihood (ML) regression estimator (solid square with solid line), and the nonlinear least squares (NLS) estimator (solid triangle with dashed line). The result shows that the NLS regression estimator is as robust as the difference-in-means estimator.

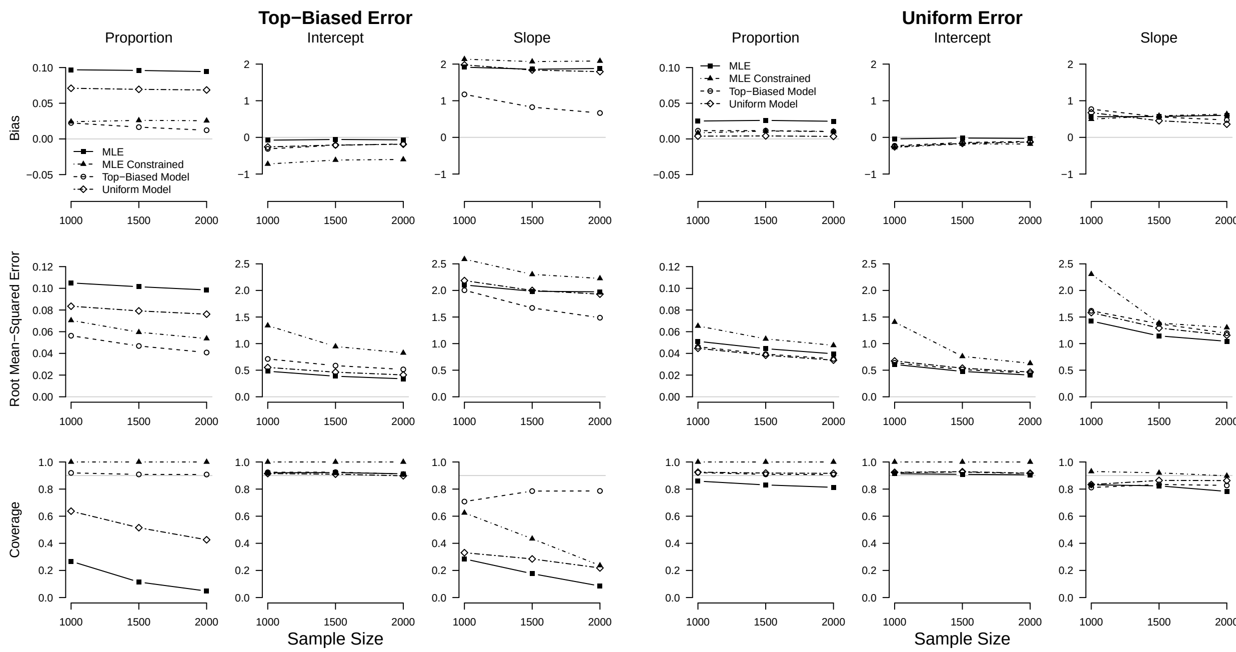

Figure A.3: Robustness of the Constrained Maximum Likelihood and Measurement Error Maximum Likelihood Estimators in the Presence of Response Errors when the Propensity of Sensitive Trait is Low for $J = 4$. We consider the four estimators of the prevalence of the sensitive trait and slope and intercept regression coefficients: the standard maximum likelihood (ML) estimator (solid square with solid line), the constrained ML estimator (solid triangle with dot-dash line), the ML estimators adjusting for top-biased response error (open square with dashed lines) and uniform response errors (open diamond with dot-long-dash line). The result shows that both the constrained MLE estimator and the models adjusting for response error are an improvement over the performance of the MLE estimator.

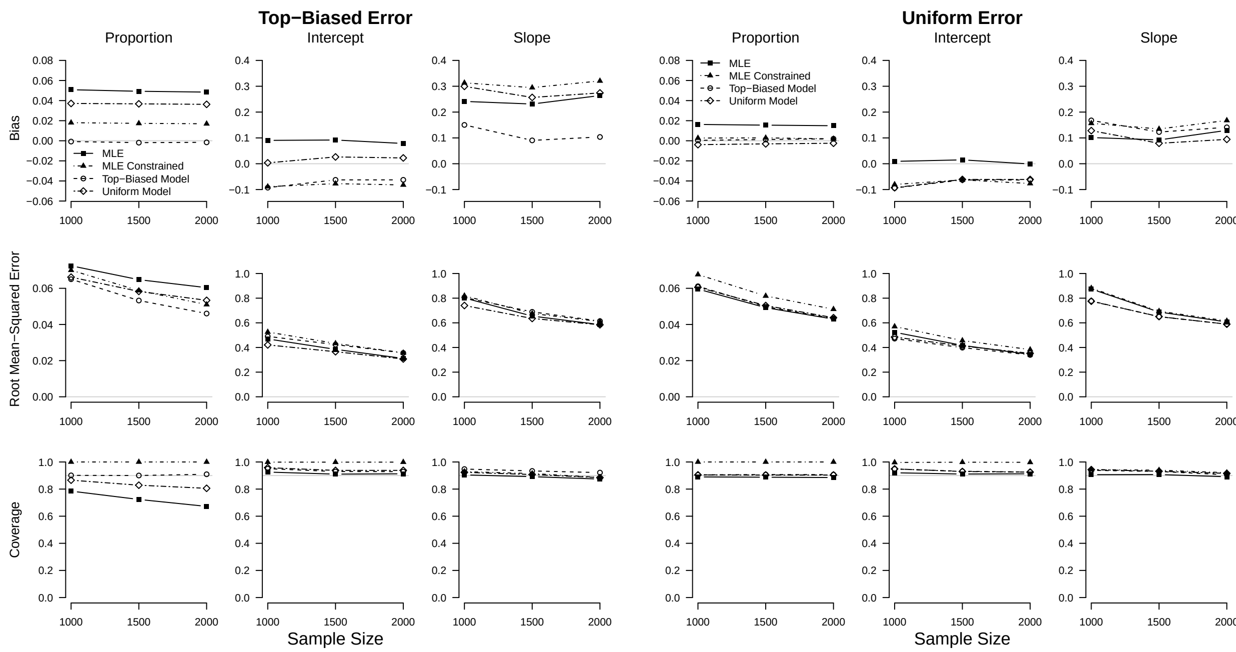

Figure A.4: Robustness of the Constrained Maximum Likelihood and Measurement Error Maximum Likelihood Estimators in the Presence of Response Errors when the Propensity of Sensitive Trait is High for $J = 4$. We consider the four estimators of the prevalence of the sensitive trait and slope and intercept regression coefficients: the standard maximum likelihood (ML) estimator (solid square with solid line), the constrained ML estimator (solid triangle with dot-dash line), the ML estimators adjusting for top-biased response error (open square with dashed lines) and uniform response errors (open diamond with dot-long-dash line). The result shows that both the constrained MLE estimator and the models adjusting for response error are an improvement over the performance of the MLE estimator.