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Assessing Bias in Regression Estimates Using Monte Carlo Simulations: Examples in Criminal Justice Research

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The Problem

Can we trust published results?

Problems with bias in reported results:

- "Do social scientists even know anything?"
- Failed replications ("repligate").[2]
- Inaccurate inferences about important relationships (Type I and Type II errors).
- Inaccurate power analyses for future studies.

To avoid these problems, researchers need tools to rigorously evaluate statistical models.

The Monte Carlo method[11] is one tool that can be used to evaluate bias in model estimates.

Monte Carlo Simulations

Monte Carlo simulations (MCS) may be described as "… the use of repeated sampling to determine the properties of a behavior or activity of interest."[9]

MCS are often used by methodologists to evaluate analytical methods and issues. For example, the impact of…

- Nonnormal residual distribution in multilevel models.[10]
- Uncorrected measurement error in path analysis.[4]
- Duplicates in survey response data.[15]
- Low degrees of freedom on structural equation model fit indices.[6]

Basic steps:

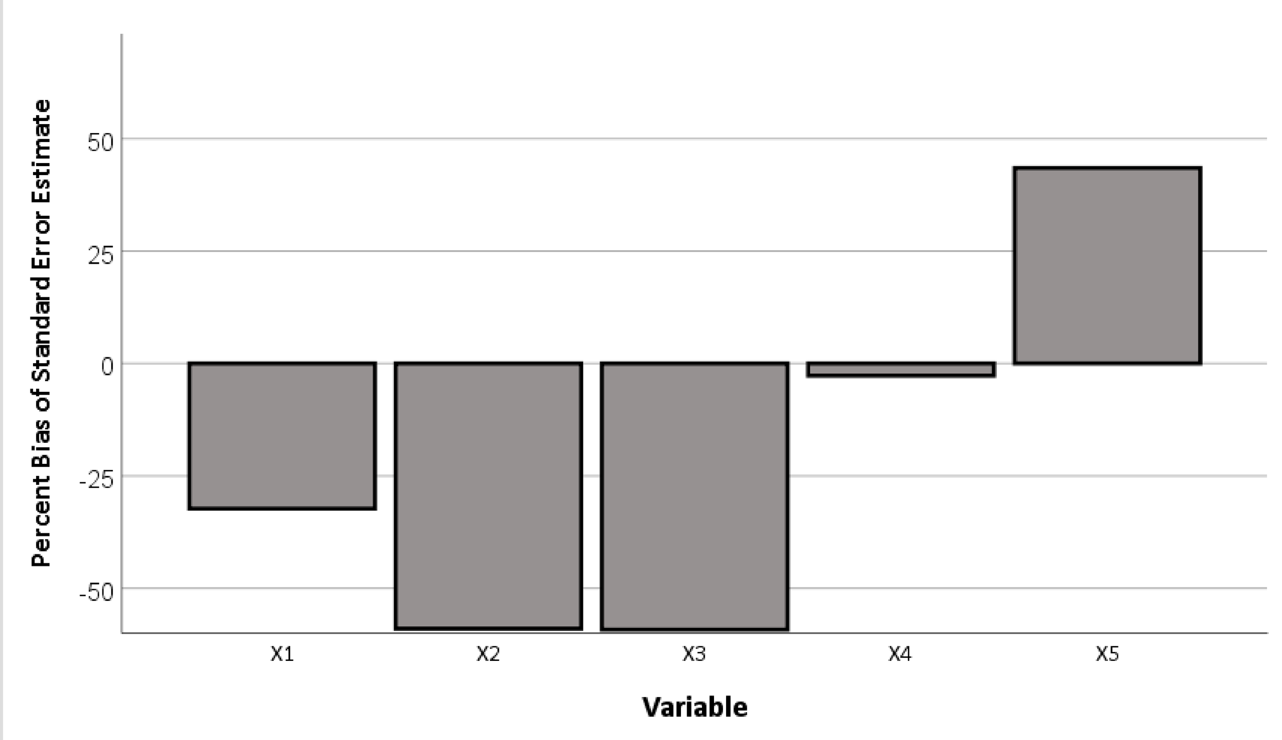
1. Generate data with desired properties.
2. Analyze data.
3. Repeat Step 1 and Step 2 thousands of times (2,500 in these examples).

Example 1: Hypothetical Study

We used a subset of real data[13,14,16] to conduct a hypothetical study. We analyzed the data with ordinary-least-squares estimation.

Data issue: Residual dependency, which leads to inaccurate standard errors and confidence intervals.[3]

The graph below shows the percent bias of the standard error estimates ($[SE_{orig}$-$SD_{sim}]/SE_{orig}$ * 100) for the five variables in the regression model.



Example 2: Published Study

We evaluate a published ordinary-least-squares regression model.[17]

Data issue: Unreliable dependent variable, which can result in biased beta coefficients.[3]

β_{orig} (*SE*) = Original (beta) coefficient and standard error.
β_{MCS} (*SD*) = Average coefficient and its standard deviation across simulations.
95% Coverage = Proportion of estimates from MCS that fell within original 95% confidence interval
% Significant = Proportion of simulations in which the coefficient was significant

Variable	β_{orig} (*SE*)	β_{MCS} (*SD*)	95% Coverage	% Significant
Gender	-.03 (.12)	-.04 (.12)	.95	.06
Race	.06 (.06)	.04 (.06)	.94	.09
Age	-.21 (.02)***	-.22 (.03)	.92	1.00
Education	.14 (.03)***	.14 (.03)	.95	1.00
Income	-.10 (.03)***	-.08 (.03)	.90	.84
Conservatism	.12 (.05)***	.15(.05)	.90	.83

Conclusion

MCS are a flexible tool for evaluating bias in model estimates.

- May help bolster legitimacy of criminal justice research.
- May benefit peer review process.
- Aligns with greater focus on interval estimates and "practical significance."[1,5,7]

Other applications of MCS:

- Forecasting.
- Incorporating data uncertainty into model estimation.[8]
- Theoretical experiments.[10,4,15,6]

Key limitation

- Results from MCS are valid insofar as the theoretical assumptions underpinning the MCS are valid.[8]

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