Appendix 2: Statistical Simulation Explained

Statistical Simulation

What is statistical simulation?

‘Statistical simulation’ refers to estimating specific quantities of interest about a researcher’s dependent variable, by applying simulation techniques to a statistical model. For example, how many evacuees per capita does a city experience given high linking social capital, but otherwise average traits? This technique was developed in the early 2000s (King et al. 2000), implemented in the Clarify package in Stata (Tomz et al. 2001), implemented in R in the *Zelig* package (Imai et al. 2008), and given improved functionality in 2017 (Choirat et al. 2017). Simulation has been applied to hundreds of different social science studies, used to visualize models of political behavior (Klofstad et al. 2013), diffusion of institutions (Bush 2011), and electoral outcomes (Panagopoulos 2021), as well as the topics of this study, disaster outcomes (Aldrich 2019) and evacuation outcomes (Fraser et al. 2021b), among others.

How does simulation work?

What does statistical simulation entail? In **Figure A2.1,** we visually summarize the stages of statistical simulation, we describe them below, referencing each part of the figure. Statistical simulation takes a **model equation (eg. Models 1A through 2B in Table A1.2, or the example model shown at the top of Figure A2.1)**. Then, as shown in **Step 1 in Figure A2.1,** we create 1000 versions of that model equation that are each just slightly different, approximating *estimation uncertainty*, as in the error term in the model equation. It does so by drawing model terms from a multivariate normal distribution (for precise technical details, see King et al. 2000).

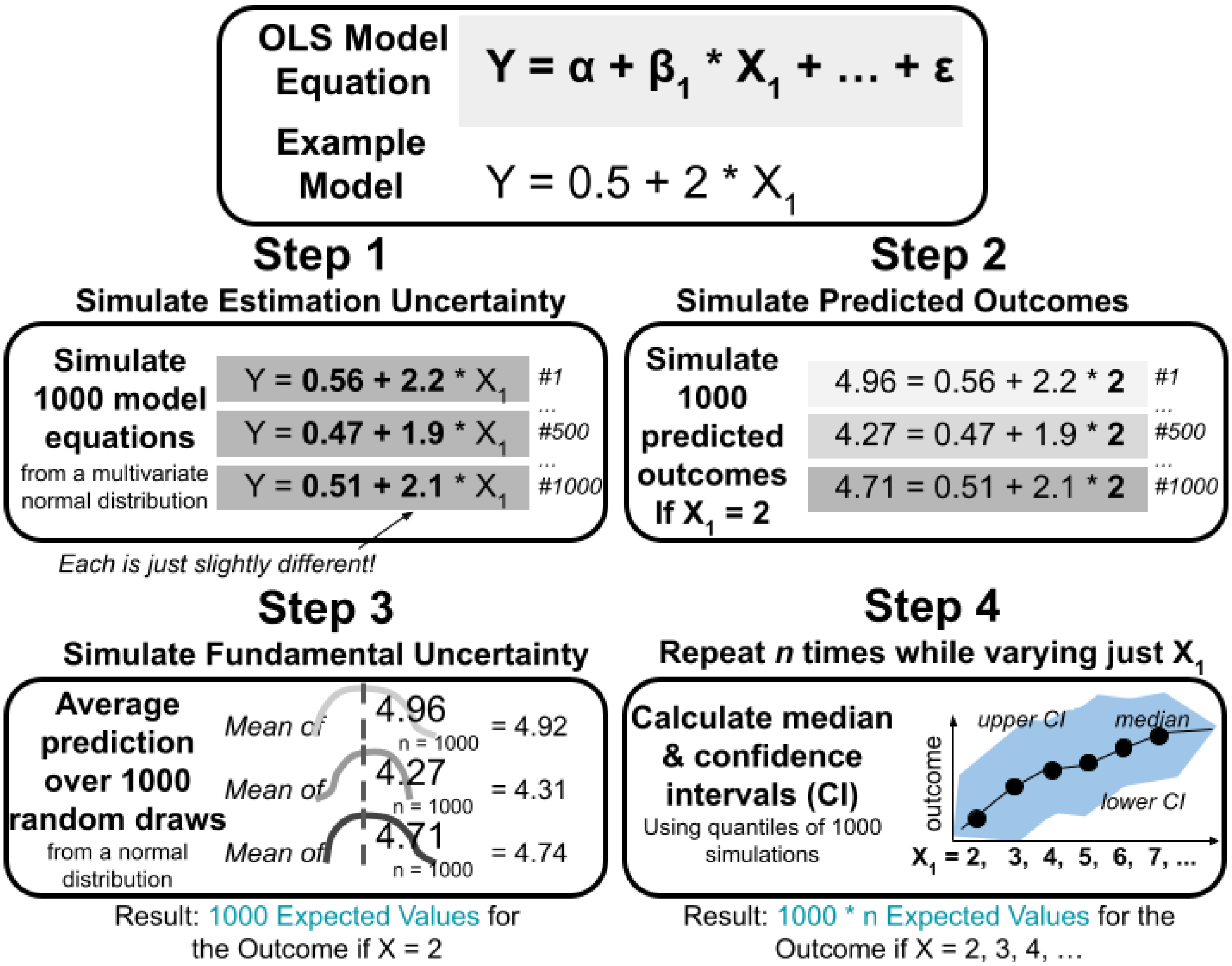
Then, in **Step 2 in Figure A2.1**, we feed those 1000 model equations the same observed data, such as the traits of an average city (eg. mean distance from epicenter, mean buildings damaged per capita). This produces 1000 simulated predicted outcomes.

In **Step 3 in Figure A2.1,** for each prediction, we take the average of 1000 random draws from a normal distribution, producing 1 expected value that accounts for *fundamental uncertainty.* Applying this strategy to each of the 1000 simulated predictions produces 1000 simulated expected values, given the set of city traits fed into the model.

Finally, we can then take those 1000 simulated values and calculate various quantities of interest using them, such as the median or confidence intervals. These 1000 expected values for our models with logged outcome variables can be exponentiated to provide expected values in the original observed units of evacuation rates. This is the standard process for generating expected values in the Zelig package in R. The Zelig package in R does this entire process automatically, after feeding the model a set of average traits.

The main power of simulation comes from showing *how much the expected outcome changes* when the researcher alters a single trait of a city, holding all else constant. This is depicted in **Step 4 in Figure A2.1,** where we visualized simulated expected effects when the trait $X_1 = 2, 3, 4, 5$, etc. For example, we show the same process in **Figure 4,** simulating changes in evacuation when the level of linking social capital is increased from its minimum to maximum observed value, holding all else constant at their means or modes. In **Figures 5 and 6,** we take this a step further, adjusting two or more variables at the same time to demonstrate interaction effects.

Figure A2.1: Visual Summary of Statistical Simulation



What is the value added from simulation?

There are two main kinds of value added from statistical simulation:

First, while other studies in the past used beta coefficients or odds ratios to express the effects of their models, these can be unintuitive. This is especially the case for this study's models, where the outcome has been log-transformed, meaning that beta coefficients represent log-odds, and when interaction effects are involved. For years, scholars have recommended marginal effects or simulated effects in order to show the precise results of an interaction effect (Kam and Franzese 2007). Simulation allows us to visualize these interaction effects on the outcome, in its original units. Identifying whether an effect is positive, negative, or meaningfully large, can be challenging using just beta coefficients or odds ratios in this circumstance. Instead, techniques like simulation (and its close cousin, marginal effects) provide precise estimates of the outcome of interest, with confidence intervals.

Second, simulation allows us to visualize effects with many different levels of confidence (90%, 95%, 99%, etc.), without relying on standard errors or p-values, which have numerous assumptions that are not always true (Ziliak and McCloskey). Because simulation relies on prediction and approximates uncertainty via simulating from a multivariate normal distribution, standard error and the assumption of independence of observations is not involved. As a result, simulation is unaffected by heteroskedasticity, making it more robust than evaluating the statistical significance of a beta coefficient's p-values, which can be suspect in the face of correlated residuals (King et al. 2000). For more information on statistical simulation, please consult the original paper (King et al. 2000) and later applications (Imai et al. 2008, Choirat et al. 2017).

References for Appendix 2

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