Everything on the Table

Demystifying the Results of Simulation Studies and Other Complex Tables

> Matthew Sigal York University

February 29th, 2016



Introduction

This presentation will outline my current dissertation research.

Primary Goals

- ► Introduce Monte Carlo designs
 - ► What? Why? How?
 - ► How are results typically presented?
- ► Use this as a springboard for a discussion on how such presentations might be improved.
- ► Provide an R package, SimDisplay that integrates with SimDesign and extends ggplot2 to aid in this endeavor.

This project is currently in the proposal stage, so feedback would be greatly appreciated!

Monte Carlo Designs...

Monte Carlo Simulation Studies (MCSS) provide a pivotal foundation for research in Quantitative Psychology, and in applied statistics at large.

They have been used to:

► Assess the performance of the RMSEA in SEM models with small degrees of freedom (Kenny et al., 2015)

Monte Carlo Designs...

Monte Carlo Simulation Studies (MCSS) provide a pivotal foundation for research in Quantitative Psychology, and in applied statistics at large.

They have been used to:

- ► Assess the performance of the RMSEA in SEM models with small degrees of freedom (Kenny et al., 2015)
- ► Examine the effects of skewness and kurtosis in linear mixed models (Arnau et al., 2013)

Monte Carlo Designs...

Monte Carlo Simulation Studies (MCSS) provide a pivotal foundation for research in Quantitative Psychology, and in applied statistics at large.

They have been used to:

- ► Assess the performance of the RMSEA in SEM models with small degrees of freedom (Kenny et al., 2015)
- ► Examine the effects of skewness and kurtosis in linear mixed models (Arnau et al., 2013)
- ▶ Investigate the behaviour of statistics (such as Pearson's *R*) at various sample sizes (Schönbrodt and Perugini, 2013)

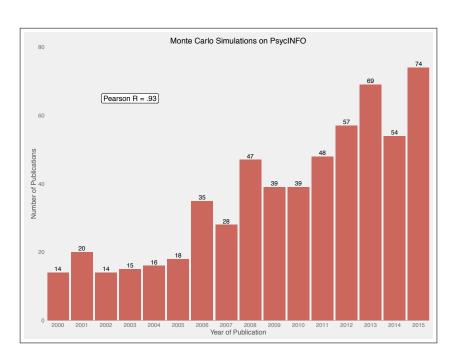
... are here to stay!

MCSS are used in a wide variety of fields and for many purposes:

- ► To help estimate if lower income areas have more pedestrian casualties (Noland et al., 2013)
- ► To create projections of teen pregnancy rates (Sayegh et al., 2010)

Within Psychology

A cursory search for **peer reviewed** articles using the search string all("Monte Carlo Simulation") in **scholarly journals** on **PsycINFO** alone yielded an evident relationship...



Within Psychology

MCSS are especially prevalent in the pages of *Multivariate* Behavioral Research and Structural Equation Modeling (SEM). In fact, these two journals have printed essential guides for researchers:

► Skrondal (2000): Design and analysis of Monte Carlo experiments: Attacking the conventional wisdom

Within Psychology

MCSS are especially prevalent in the pages of *Multivariate*Behavioral Research and Structural Equation Modeling (SEM). In fact, these two journals have printed essential guides for researchers:

- ► Skrondal (2000): Design and analysis of Monte Carlo experiments: Attacking the conventional wisdom
- ► Paxton, Curran, Bollen, et al. (2001): Monte Carlo experiments: Design and implementation

Within Psychology

MCSS are especially prevalent in the pages of *Multivariate*Behavioral Research and Structural Equation Modeling (SEM). In fact, these two journals have printed essential guides for researchers:

- ► Skrondal (2000): Design and analysis of Monte Carlo experiments: Attacking the conventional wisdom
- ► Paxton, Curran, Bollen, et al. (2001): Monte Carlo experiments: Design and implementation
- ► Boomsma (2013): Reporting Monte Carlo studies in *Structural Equation Modeling*

Monte Carlo Simulation Studies

What are Monte Carlo Simulation Studies? Why do we care?

MCSS are **experiments** in which certain parameters, which are known and fixed by the researcher, are used to generate random data and then estimate the behavior of other statistics. This is repeated over many *iterations*, and across many *conditions*.

Monte Carlo Simulation Studies

For example, we could:

- ► Evaluate the performance of a new statistic
- ► Investigate the performance of a statistic under various assumption violations
- ► Determine Power or Type I error rates for various designs
- Determine how well we recover parameters under various conditions
- ► Simulate 'realistic' data to address hard to study phenomena

Monte Carlo Simulation Studies

For SEM in particular, MCSS are an excellent approach for evaluating estimators and goodness-of-fit statistics under a variety of conditions, model complexity, and model misspecification.

As stated by Paxton et al., "... many topics in SEM would benefit from an empirical analysis through Monte Carlo methods" (2001, p. 288).

Conducting MCSS Research

- 1. Develop a theoretically derived research question
- 2. Create a valid model
- 3. Design specific experimental conditions
- 4. Choose values for the population parameters
- 5. Choose an appropriate software package
- 6. Execute the simulation and repeat
- 7. Determine a file storage solution
- 8. Troubleshoot and verify
- 9. Summarize results

Brief Example

Can we use likelihood difference approach to detect differential item functioning for multi-dimensional IRT models?¹

- Investigate false detection rates (FDR, or type I DIF tests for detecting no difference between groups), where the underlying item structure for all items is equivalent across the two groups.
- Investigate power, where a true difference exists for the slope of one or more particular items across the groups on one of the underlying factors.

¹Sigal and Chalmers, forthcoming.

Brief Example

Four design variables were explored to determine their effect on detection rates:

- ▶ number of items (10, 15, 30)
- ► sample size per group (250, 500, 1000, 2000)
- ▶ number of items with DIF (0, 1, 2, or 3)
- for the conditions with DIF, also manipulated the amount of DIF (medium or small)

Final Design

After removing redundant cells, we have 12 FDR and 72 DIF conditions: 84 total cells.

MCSS Presentation

How are results from such designs presented? Are they done in a meaningful way?

In previous work, methods for conveying the findings from MCSS have been given little attention.

For instance, Paxton et al. (2001) state that results can be presented descriptively, graphically, and inferentially but provide little detail on how to do so.

MCSS Presentation

"...reading results from Monte Carlo studies in whatever form should be a revelatory task, not a baffling puzzlement."

-Boomsma, 2013, p. 534.

Prototypical Results

The following table is from Ramsey & Ramsey (2009), presented in the *British Journal of Mathematical and Statistical Psychology*.

Straight forward simulation design:

- ► Goal:
 - ► to compare the performance of 10 pairwise multiple comparison procedures (MCPs)
- ► Design:
 - ▶ degree of heteroskedasticity (*c*, equal variance, and multiplied by 2, 4, and 10)
 - ▶ number of groups (k, from 4 to 8)
 - ► sample size per group (n, from 2 to 500)
- ► Primary output:
 - ► Type I error rates from full true null models

Т3 C GH GF* PF* GH9 GH8 GH7 GH6 GH5 (a) c = 1.0117 .0445 .0048 .0039 .0368 .0313 .0260 .0197 .0158 .0397 .0135 .0512 .0137 .0171 .0439 .0385 .0331 .0272 .0216 .0157 .0186 .0256 .0450 .0388 .0335 .0283 .0391 .0514 .0234 5 .0383 .0173 .0499 .0216 .0311 .0446 .0379 .0328 .0265 .0218 .0426 .0231 .0536 .0286 .0371 .0472 .0426 .0375 .0309 .0253 7 .0388 .0239 .0497 .0259 .0351 .0434 .0386 .0338 .0295 .0252 8 .0446 .0301 .0534 .0305 .0373 .0479 .0443 .0391 .0342 .0292 9 .0410 .0263 .0511 .0301 .0390 .0460 0407 .0360 .0290 .0238 10 .0471 .0343 .0562 .0363 .0441 .0518 .0468 .0410 .0353 .0291 ш 0417 .0313 .0531 .0326 .0423 .0464 .0412 .0368 .0311 .0256 12 0423 .0333 .0518 .0342 0433 0470 .0422 .0376 .0317 .0261 13 .0446 .0371 .0545 .0367 .0440 .0488 .0439 .0390 .0344 .0295 14 .0367 .0525 .0338 .0381 .0439 .0436 .0474 .0437 .0333 .0274 .0430 .0401 .0517 .0387 .0479 .0473 .0417 .0369 .0321 .0269 24 .0422 .0406 .0510 .0383 .0475 .0469 .0414 .0367 .0323 .0284 28 .0405 .0400 .0496 .0371 .0467 .0448 .0397 .0354 .0301 .0249 29 .0402 .0391 .0356 .0387 .0333 .0288 .0236 .0472 .0426 .0436 30 .0416 .0408 .0510 .0398 .0498 .0456 0402 .0361 .0305 .0248 31 .0436 .0432 .0525 .0406 .0478 .0477 .0418 .0369 .0311 .0257 32 .0427 .0425 .0513 .0388 .0467 .0474 .0411 .0365 .0320 .0269 33 .0365 .0364 0457 .0333 .0425 .0394 .0352 .0312 .0260 .0214 34 .0467 .0469 .0546 .0430 .0460 .0413 .0360 .0517 .0506 .0301 35 .0409 .0413 .0488 .0361 .0434 .0436 .0397 .0344 .0287 .0234 36 .0431 .0440 .0527 .0402 .0480 .0463 .0418 .0367 .0322 .0264 37 .0412 .0420 .0495 .0377 .0442 .0448 .0395 .0359 .0310 .0249 38 .0423 .0439 .0521 .0375 .0459 .0465 .0408 .0351 .0295 .0246 39 .0446 .0461 .0545 .0403 .0485 .0485 .0435 .0381 .0325 .0274 40 .0405 .0425 .0487 .0383 .0467 .0445 .0394 .0353 .0290 .0245 50 .0496 .0520 .0581 .0457 .0528 .0534 .0481 .0416 .0356 .0303 60 .0417 .0448 .0506 .0391 .0460 .0452 .0402 .0358 .0314 .0259 70 .0401 .0438 .0482 .0384 .0462 .0437 .0392 .0340 .0284 .0236 0437 .0491 0534 .0440 .0517 .0486 0430 .0376 .0328 .0277 100 .0431 .0484 .0517 .0415 .0484 .0469 .0419 .0371 .0324 .0269 200 .0421 .0498 .0515 .0419 .0500 .0462 .0411 .0363 .0318 .0283 300 .0430 .0489 0499 .0423 .0500 .0464 .0421 .0374 .0317 .0265 400 .0392 .0463 .0464 .0395 .0464 .0426 .0382 .0346 .0300 .0251 500 .0450 .0534 .0537 .0452 .0517 .0480 .0439 .0394 .0344 .0296 Max .0791 .0534 .0581 .0457 .0528 .0534 .0481 .0416 .0360 .0303 (b) c = 2.0898 .0109 .0512 .0073 .0056 .0407 .0321 .0253 .0209 .0167

.0367

.0384

.0310 .0259

.0324 .0270

.0585

.0563

.0156 .0199 .0515 .0430

.0283

.0440 .0502 .0444

3 .0451 .0158

6

14 .0383 .0348 .0449 .0261 .0443 .0420 .0379 .0335 .0280 .0226

21 .0427 .0424 .0525 .0298 .0485 .0475 .0418 .0370 .0312 .0263

.0478 .0225 .0598 .0240 .0324 .0531 .0469 .0402 .0357 .0292

.0467 .0247 .0586 .0267 .0418 .0519 .0460 .0405 .0345 .0282

.0448

.0433 .0288 .0543 .0293 .0438 .0491 .0431 .0382 .0329 .0271

.0275

Table 1. Type I errors for 10 MCPs at $\alpha = .05$, k = 4, equal n_b variance multiplier c and a true full null

hypothesis

n	T3	С	GH	GF*	PF*	GH9	GH8	GH7	GH6	GH5
25	.0391	.0394	.0456	.0267	.0430	.0411	.0380	.0337	.0295	.0250
26	.0418	.0437	.0506	.0299	.0465	.0457	.0413	.0365	.0315	.0249
27	.0424	.0435	.0527	.0320	.0472	.0470	.0413	.0354	.0317	.0262
28	.0393	.0408	.0465	.0269	.0439	.0434	.0382	.0336	.0289	.0235
29	.0398	.0409	.0481	.0285	.0447	.0434	.0388	.0348	.0296	.0246
30	.0395	.0410	.0470	.0269	.0426	.0419	.0383	.0333	.0287	.0238
31	.0427	.0434	.0497	.0299	.0466	.0451	.0417	.0364	.0326	.0279
32	.0393	.0418	.0490	.0280	.0457	.0436	.0387	.0339	.0297	.0247
33	.0402	.0422	.0479	.0286	.0462	.0440	.0393	.0353	.0298	.0249
34	.0396	.0414	.0471	.0256	.0429	.0430	.0378	.0341	.0290	.0249
35	.0425	.0450	.0498	.0303	.0490	.0457	.0411	.0362	.0313	.0266
Max	.0898	.0450	.0598	.0320	.0490	.0531	.0469	.0405	.0357	.0292
(c) c =	= 4									
2	.1195	.0179	.0689	.0133	.0120	.0566	.0464	.0387	.0322	.0267
3	.0618	.0291	.0742	.0241	.0306	.0670	.0600	.0520	.0457	.0397
4	.0513	.0299	.0623	.0238	.0334	.0567	.0504	.0440	.0385	.0328
5	.0502	.0341	.0609	.0246	.0378	.0550	.0494	.0437	.0382	.0311
6	.0436	.0317	.0547	.0203	.0364	.0489	.0432	.0355	.0308	.0270
7	.0397	.0330	.0489	.0219	.0390	.0440	.0396	.0350	.0302	.0254
8	.0402	.0336	.0507	.0213	.0379	.0450	.0401	.0350	.0296	.0247
9	.0419	.0378	.0516	.0242	.0410	.0469	.0416	.0365	.0309	.0261
10	.0390	.0371	.0494	.0233	.0427	.0440	.0389	.0341	.0289	.0248
11	.0404	.0379	.0479	.0205	.0369	.0443	.0400	.0350	.0297	.0253
12	.0388	.0377	.0467	.0210	.0403	.0419	.0384	.0342	.0291	.0239
13	.0388	.0387	.0480	.0220	.0423	.0436	.0386	.0349	.0298	.0246
14	.0395	.0395	.0482	.0206	.0400	.0434	.0391	.0350	.0303	.0247
15	.0365	.0370	.0454	.0208	.0413	.0403	.0361	.0307	.0267	.0218
16	.0335	.0351	.0414	.0186	.0354	.0378	.0328	.0290	.0253	.0212
17	.0359	.0386	.0443	.0189	.0361	.0405	.0356	.0311	.0269	.0229
18	.0380	.0398	.0460	.0201	.0409	.0414	.0378	.0322	.0279	.0236
21	.0392	.0419	.0473	.0203	.0417	.0423	.0388	.0341	.0280	.0229
28	.0337	.0373	.0424	.0187	.0381	.0376	.0325	.0273	.0228	.0188
35	.0366	.0376	.0422	.0196	.0398	.0371	.0357	.0316	.0273	.0228
Max	.1195	.0450	.0742	.0320	.0490	.0670	.0600	.0520	.0457	.0397
(d) c =		.0150	.07 12	10020	10 17 0	.0070	.0000	.0020	.0 101	.0077
2	.1555	.0351	.0964	.0268	.0266	.0823	.0708	.0595	.0520	.0431
3	.0686	.0434	.0831	.0285	.0359	.0747	.0660	.0602	.0523	.0440
4	.0530	.0389	.0641	.0250	.0381	.0581	.0516	.0460	.0400	.0328
5	.0476	.0406	.0578	.0224	.0346	.0527	.0466	.0419	.0367	.0306
6	.0417	.0381	.0525	.0215	.0343	.0473	.0414	.0362	.0309	.0260
7	.0394	.0385	.0492	.0181	.0319	.0435	.0390	.0343	.0293	.0243
8	.0371	.0370	.0469	.0184	.0340	.0416	.0371	.0323	.0280	.0241
9	.0327	.0351	.0439	.0180	.0359	.0382	.0325	.0287	.0250	.0207
10	.0358	.0379	.0441	.0173	.0346	.0401	.0357	.0314	.0266	.0226
11	.0338	.0371	.0431	.0173	.0364	.0375	.0337	.0304	.0266	.0226
12	.0350	.0379	.0430	.0179	.0358	.0389	.0350	.0310	.0263	.0226
13	.0327	.0368	.0414	.0172	.0363	.0376	.0330	.0288	.0247	.0206
14	.0357	.0390	.0433	.0172	.0349	.0390	.0356	.0300	.0256	.0218

.0152 .0354 .0363

.0312

.0283 .0242

.0205

Table I (Centinued)

21

.0319 .0369 .0398

...and it is still going!

n	T3	C	GH	GF*	PF*	GH9	GH8	GH7	GH6	GH5
27	.0315	.0369	.0397	.0161	.0352	.0347	.0312	.0277	.0230	.0196
Max	.1555	.0434	.0964	.0285	.0381	.0823	.0708	.0602	.0523	.0440
Max	.1555	.0534	.0964	.0457	.0528	.0823	.0708	.0602	.0523	.0440

Note. T3, Dunnett; C, Cochran; GH, Games-Howell; GF*, Games-Howell and Brown-Forsythe F; PF*, Peritz-Brown-Forsythe F; GH9, GH applied at 0.9α ; GH8, GH at 0.8α ; GH7, GH at 0.7α ; GH6, GH at 0.6α ; GH5, GH at 0.5α .

Even so, this table ignores:

- ► Many of the sample size comparisons
 - ▶ none of the (many) sample size conditions that pertain to unequal groups
- ► The number of groups factor...
 - this entire table only refers to k = 4!

So. . .

- ► MCSS designs are important.
- ▶ Presenting results via tables is the classic approach
- ► ... however, presenting the results in this manner might not be very illuminating.

Dissertation

- Primary goal is to catalogue and improve methods for finding trends in complex tables, such as those from MCSS designs
- Take principals from information design theory
- Apply these findings across three broad categories of approaches:
 - ► Improving Static Tables
 - ► Graphical Approaches
 - ► Interactive Approaches
- ► Provide an R package, SimDisplay that integrates with SimDesign to make such presentations easy.

Static Methods

Static tables can convey substantial amounts of information and should still be recognized as a suitable method for presenting MCSS results, if thoughtfully constructed.

Recommendations

- ► Use emphasis to signify important results (bold, italics)
- ► If possible, use color for added impact
- Present the rows and columns in a meaningful way
 - ► Use effects ordering and/or rotation (e.g., manipulate rows using clustering algorithms)

Table 1: ... and this is only 12 of the 72 rows!

N	Items	nDIF	sDIF	Average P	Percent < .05
250	10	2	1	0.13	0.66
500	10	2	1	0.08	0.8
1000	10	2	1	0.05	0.87
2000	10	2	1	0.03	0.93
250	15	2	1	0.09	0.76
500	15	2	1	0.05	0.85
1000	15	2	1	0.04	0.9
2000	15	2	1	0.02	0.95
250	30	2	1	0.07	0.82
500	30	2	1	0.05	0.87
1000	30	2	1	0.03	0.93
2000	30	2	1	0.02	0.96

Detection rates by sample size and number of items in the situation where 2 items should exhibit large DIF.

Table 2: Sorted by Sample Size

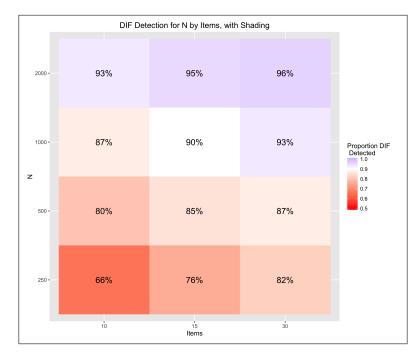
N	Items	nDIF	sDIF	Average P	Percent < .05
250	10	2	1	0.13	0.66
250	15	2	1	0.09	0.76
250	30	2	1	0.07	0.82
500	10	2	1	0.08	0.8
500	15	2	1	0.05	0.85
500	30	2	1	0.05	0.87
1000	10	2	1	0.05	0.87
1000	15	2	1	0.04	0.9
1000	30	2	1	0.03	0.93
2000	10	2	1	0.03	0.93
2000	15	2	1	0.02	0.95
2000	30	2	1	0.02	0.96

Graphical Methods

As with many statistical analyses, graphical methods should be utilized for exploring MCSS results.

Such methods range from stylized presentation of the raw table:

- e.g., heatmaps/tableplots with exact values overlaid
- ► Created with sensible values for shading
- ► For designs with 3 or more dimensions, utilize marginal tables or facet to see various relationships



Graphical Methods

Considering how large these tables can be, it is useful to think of graphical approaches that make it easier to see what is happening.

- ► Extend the tableplot framework (Kwan et al., 2009)
 - semi-graphic display that uses both numbers and symbols (with sizes, colors, shapes providing additional information)
 - originally designed for EFA/CFA, but underlying idea can be extended.
- ► Treat simulation conditions as ANOVA designs
 - ► so-called 'meta-models'
 - utilize effect plots for the design variables
- ► Utilize dimension reduction techniques, such as hypothesis-error (HE) plots (Friendly, 2007)
 - Design cells presented as points on graphic

Interactive Methods

The above methods are worth pursuing for showing static slices of our results, but it would be better to be able to manipulate the data on the fly.

Interactive displays allow for the dynamic exploration of complex tables and figures. Such a display could allow for changes in:

- sorting and filtering of variables
- ▶ incorporating shading or altering the scale
- ▶ live search
- ▶ pop-up text (e.g., cell identification on HE plot)

SimDisplay

Some of these ideas have already been implemented in SimDisplay.

Utility Functions:

- get_design_levels() and get_sim_levels(): Extract design and result vectors from dataframe.
- sim_design_check(): Check properties of SimDesign dataframe and return for analysis

Core Features:

- ► convert_df(): Convert a dataframe to a SimDesign object.
- ▶ generic plot() method: quick access to various faceted views of a dataframe
- ftable() and xtable() methods: formatted output for static numerical tables (either to console or to LaTeX)
- tableplot() method to generate static semi-graphic displays
- ▶ shinySim() takes a SimDesign dataframe and creates an interactive applet.

SimDisplay

SimDisplay includes a dataframe object, tsimresults, with the results of a small simulation study on how the *t*-statistic behaves under various sample size, group size, and standard deviation ratio conditions, when evaluated with and without the Welch correction.

```
devtools::install_github("mattsigal/SimDisplay")
library(SimDisplay)
data(tsimresults)
str(tsimresults)
head(tsimresults)
library(shiny, quietly = TRUE)
runApp(shinySim(tsimresults))
```

Thank you!

Slides available at: www.matthewsigal.com/teaching

- Arnau, J., Bendayan, R., Blanca, M. J., and Bono, R. (2013). The effects of skewness and kurtosis on the robustness of linear mixed models. *Behavioural Research*, 45(3):873–879.
- Boomsma, A. (2013). Reporting Monte Carlo studies in Structural Equation Modeling. *Structural Equation Modeling*, 20:518–540.
- Friendly, M. (2007). HE plots for multivariate linear models. *Journal of Computational and Graphical Statistics*, 16(2):421–444.

 Kenny, D. A., Kaniskan, B., and McCoach, D. B. (2015). The
 - performance of RMSEA in models with small degrees of freedom. Sociological Methods & Research, 44(3):486–507.

 Kwan, E., Lu, I. R. R., and Friendly, M. (2009). Tableplot: A new tool for assessing precise predictions. Zeitschrift für Psychologie /

Journal of Psychology, 217(1):38–48.

Noland, R. B., Klein, N. J., and Tulach, N. K. (2013). Do lower income areas have more pedestrian casualties? *Accident Analysis and Prevention*.

- Paxton, P., Curran, P. J., Bollen, K. A., Kirby, J., and Chen, F. (2001). Monte Carlo experiments: Design and implementation. *Structural Equation Modeling*, 8(2):287–312.
- Ramsey, P. H. and Ramsey, P. P. (2009). Power and Type I errors for pairwise comparisons of means in the unequal variances case. *British Journal of Mathematical and Statistical Psychology*,

62:263-281.

- Sayegh, M. A., Castrucci, B. C., Lewis, K., and Hobbs-Lopez, A. (2010). Teen pregnancy in Texas: 2005 to 2015. *Maternal and Child Health Journal*, 14(1):94–101.
- Schönbrodt, F. D. and Perugini, M. (2013). At what sample size do correlations stabilize? *Journal of Research in Personality*, 47(5):609–612.
- Skrondal, A. (2000). Design and analysis of Monte Carlo experiments: Attacking the conventional wisdom. *Multivariate Behavioral Research*, 35(2):137—167.