Testing Mediation in Structural Equation Modeling: The Effectiveness of the Test of Joint Significance

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Abstract

A large number of approaches have been proposed for estimating and testing the significance of indirect effects in mediation models. In this study, four sets of Monte Carlo simulations involving full latent variable structural equation models were run in order to contrast the effectiveness of the currently popular bias-corrected bootstrapping approach with the simple test of joint significance approach. The results from these simulations demonstrate that the test of joint significance had more power than bias-corrected bootstrapping and also yielded more reasonable Type I errors.

Keywords

mediation, indirect effects, SEM, bias-corrected bootstrapping, simulation

The specification of *indirect effects* is a key aspect of both path analysis and latent variable structural equation models (perhaps even their *raison d'être*). An indirect effect occurs when the effect of one variable (either observed or latent) on a second is *mediated*, in whole or part, by one or more other intervening variables (Brown, 1997). For the case involving a single intervening variable, an initial predictor variable significantly accounts for variation in an intervening variable, referred to as a mediator. The mediator, in turn, significantly accounts for variation in an outcome

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variable. Under such conditions, the amount of unique variance in the outcome variable accounted for by the initial variable is necessarily smaller than it would have been if the intervening variable had been ignored. Hence, indirect effects refer to compound structural paths made up of two or more direct variable-to-variable paths.

For example, consider the structural path model represented in Figure 1. In this model, among other effects, only a direct effect of temperament on externalizing behavior is hypothesized while both direct and indirect effects of neighborhood on externalizing behavior are assumed to be present. Moreover, the total indirect effect of neighborhood on externalizing behavior is actually made up of three specific indirect effects involving compound paths running through maternal depression only, through parenting style only, and through both maternal depression and parenting style.

With respect to testing the significance of indirect effects, a number of methods for statistically verifying the presence of mediation have been proposed over the past 30 years. Such methods include the regression-based conditions of the classic Baron and Kenny (1986; Zhao, Lynch, & Chen, 2010) *causal steps* approach, the commonly employed normal-theory *product-of-coefficients* approach originally developed by Sobel (1982; which involves comparing the ratio of the product of the component path coefficients over its standard error to a standard normal critical z value), the *distribution of the product* approach (MacKinnon, Fritz, Williams, & Lockwood, 2007; Tofighi & MacKinnon, 2011), and the currently popular *bootstrapping* approach (Shrout & Bolger, 2002; where two latter two methods involve obtaining confidence intervals for indirect effects that are more able to adequately capture the skewed, asymmetric nature of their sampling distributions). Fourteen different variants of the first three approaches were examined in a simulation study by MacKinnon, Lockwood, Hoffman, West, and Sheets (2002), and six variants of the bootstrapping approach were examined in follow-up simulation study by MacKinnon, Lockwood, and Williams (2004). The general consensus arising from this simulation work (see also M. Cheung, 2007; Hayes & Scharkow, 2014; Preacher & Hayes, 2008; Taylor, MacKinnon, & Tein, 2008; and also G. W. Cheung & Lau, 2008, who, so far, have been the only researchers to examine the differential performance of mediation testing approaches within an actual latent variable structural equation modeling [SEM] framework) is that the best method for testing indirect effects seems to be bias-corrected bootstrapping (BC bootstrapping; Shrout & Bolger, 2002).

As in all bootstrapping approaches, BC bootstrapping of the confidence intervals (CIs) for indirect effects involves taking multiple repeated samples with replacement from the data set in question. For each bootstrapped sample, the path (for observed variables) or structural equation (for latent variables) model is refit and estimates for all the parameters retained (where for indirect effects this entails a multiplication of the corresponding fitted path coefficients). After collecting all the bootstrapped results, the set of values obtained for each effect of interest are sorted and lower and upper percentile values on each sorted set of values are determined. For a standard 95% CI, these values would represent the 2.5th and 97.5th percentile values. Bias-

Figure 1. An example of a structural model specifying both direct and indirect effects.

corrected CIs, however, involve a slight adjustment of these percentile values depending on the proportion of bootstrapped values that are less than or equal to the original sample value (where explicit instructions on how to make such an adjustment can be found in Lau & Cheung, 2012). With respect to this approach, note that determining whether the resulting $(1 - \alpha)\%$ CI for an indirect effect does not contain 0 is equivalent to a two-sided, α -level hypothesis test for whether the original sample value for that indirect effect significantly differs from 0.

The main issue surrounding this consensus conclusion is a practical one. Namely, although SPSS and SAS macros are readily available for bootstrapping within simple and multiple mediation analyses involving observed variables (Preacher & Hayes, 2008), unless a SEM researcher with a “complex” latent variable model is using Mplus software (Muthén & Muthén, 2006; which does indeed provide BC bootstrapped confidence intervals for both total and specific indirect effects within such models), obtaining bootstrapped confidence intervals for *specific* indirect effects can

be problematic. For example, although users of AMOS (Arbuckle, 2003) can obtain BC bootstrapped confidence intervals for total indirect effects, requesting them for specific indirect effects is not possible. Similarly, users of LISREL (Joreskog & Sorbom, 1996) or EQS (Bentler, 2004) must either accept Sobel tests of total indirect effects or use somewhat tedious (and potentially prohibitive depending on the level of expertise of the researchers) alternative procedures to obtain BC bootstrapped results for specific indirect effects (Lau & Cheung, 2012; Mallinckrodt, Abraham, Wei, & Russell, 2006; Preacher & Hayes, 2008; see also the phantom variable approach described by M. Cheung, 2007, and Macho & Ledermann, 2011).

Given these practical concerns, we feel that it is important to determine the viability of an extremely intuitive and straightforward procedure for testing indirect effects known as the *test of joint significance* (TJS; Kenny, Kashy, & Bolger, 1998; Mallinckrodt et al., 2006). In essence, the TJS procedure is an even simpler variant of the classic causal steps approach which involves determining if the individual paths making up the compound path representing the indirect effect are all significant (i.e., based on information that is already directly available from the structural model results). If so, the corresponding indirect effect is regarded as being significant. Note that the effectiveness of this procedure for mediation models involving observed variables has indeed been examined in three of the previously reported simulation studies (Hayes & Scharkow, 2014; MacKinnon et al., 2002; Taylor et al., 2008) where, in all cases, the TJS approach fared quite well with respect to balancing both Type I error and power.

In our view, it just seems obvious that a significant indirect effect is present if the coefficients for the individual direct paths making up that effect are all significant. However, the extensive amount of work on testing indirect effects that has been published has seemingly influenced the field in such a way that many behavioral researchers (including reviewers of journal articles, academic supervisors, and thesis committee members) believe that evidence of the TJS nature is simply “not enough” to verify the *presence* of an indirect effect. Hence, in order to drive home the point that special tests for indirect effects often might not actually be needed within a SEM framework, in the following simulation work we set out to demonstrate that a significant indirect effect according to conventional BC bootstrap testing methods must necessarily be present whenever all the paths making up that effect are significant (hence, rendering the BC bootstrap test of the indirect effect completely redundant with the TJS). In doing so, we discovered that the power to determine the presence of an indirect effect in a complex latent-variable SEM model (or, at least, the ones examined in this study) was actually higher for the TJS than for conventional BC bootstrap testing methods (which can then lead to the conundrum, if such bootstrapping methods are employed, that an indirect effect might not actually be significant even though all the individual paths making up that indirect effect are significant). Relatedly, we also found that BC bootstrap testing methods tended to underestimate Type I errors involving the indirect effect (more so than the TJS approach).

Figure 2. Model 1 population values.

Figure 3. Model 2 population values.

Method

In this study, we generated simulations for two different hypothetical population versions of a structural equation model. In Model 1 (see Figure 2), all the path coefficients in the model were assumed to have moderately small, nonzero values (which is fairly representative of the sizes of the path coefficient researchers typically find in practice). Note that although these were unstandardized path coefficients, they were actually close to representing standardized ones given that the simulated residual variances of these variables were set to 1 (for instructions on how to set residual values to ensure standardized path coefficients, see Thoemmes, MacKinnon, & Reiser, 2010). In Model 2 (see Figure 3), the sizes of three of the path coefficient values at the front end of the model were doubled whereas one of the path coefficients leading to the outcome variable was set to zero. Results from Model 1 were used to examine power, given that all the paths in Figure 2 have nonzero values, and results from Model 2 were used to examine both power and Type I error given that three of the four compound paths in Figure 3 contain the direct path from parenting to externalizing, which was assigned a population value of 0 (hence, ensuring that the population value of any indirect effect containing it is 0 as well).

All the variables in Figures 2 and 3 were latent variables, each of which had five indicator variables that are not shown in the figures. For each latent variable, the

factor loading values for each of the five indicators were assumed be 1.0, 0.9, 0.8, 0.7, and 0.6, respectively (representing decreasing reliabilities across indicators). Although the latent variables all have names in Figures 2 and 3, these labels were used simply to help make the models more intuitive given their purely hypothetical nature (that being said, they do correspond to actual models tested in published work by the second author; Gallitto, 2014).

For each model, 500 data sets were generated for sample sizes of 150 and 400 simulated cases (which are quite representative of the range of actual samples sizes in many SEM studies) using Mplus Monte Carlo routines. Each set of simulated data was then fit, again using Mplus, to a structural equation model with neighborhood, depression, parenting, and externalizing as latent variables in order to obtain solutions for the set of paths in Models 1 and 2.

The main results of interest entailed a comparison, within the same simulated data sets, of the proportion of times that the full set of direct component paths within each of the four possible indirect paths in Models 1 and 2 were found to be jointly significant (at $\alpha = .05$ for each path) versus the number of times that the overall indirect paths themselves were found to be significant (at $\alpha = .05$). BC bootstrapping, based on 1,000 resamples, was used when fitting the models to determine the standard errors for each of the direct and indirect path parameters (from which a determination of whether they significantly differed from 0 could be made). The Mplus code for the two programs used to simulate Model 1 and then to fit it is given in the appendix. These programs were run 500 times for each model and sample size with different random seed values each time. Because bootstrapping is not available in the Mplus Monte Carlo routines, this fact necessitated analyzing each individual set of simulated data separately after generating it (and collating those results by hand).¹

Results

Results for each model are presented in Table 1 (where running these models with the two additional variables shown in Figure 1 included yields analogous results).² The results for Model 1, especially with respect to the indirect path containing three path components, demonstrate that the power to determine the significance of the indirect effects was higher for the TJS approach (on the left side of Table 1) than for the BC bootstrapping approach (on the right side of Table 1).³ For example, for sample sizes of $N = 400$, both paths in the compound path from neighborhood (NH) to externalizing (EX) through depression (DP; i.e., $NH \rightarrow DP \rightarrow EX$) were significant in 89.8% of the 500 simulated data sets, whereas the 95% BC bootstrapped CI for this same indirect path (in those same data sets) did not contain 0 only 78.4% of the time. Moreover, the results for Model 2 demonstrate that the probability of obtaining a Type I error for the indirect paths involving parenting was lower for the BC bootstrapping approach. Such results essentially both indicate that the BC bootstrapped interval estimates were too wide and covered 0 more than they should have.

Table 1. Simulation Results Pertaining to the Four Possible Indirect Paths in Figures 2 and 3.

		Test of joint significance: Proportion of times that the significance of all paths was <.05				Bias-corrected bootstrapping: Proportion of times that the significance of the indirect path was <.05			
		NH → DP → EX	NH → PA → EX	DP → PA → EX	NH → DP → PA → EX	NH → DP → EX	NH → PA → EX	DP → PA → EX	NH → DP → PA → EX
N = 150									
Model 1	.276		.242	.282	.182	.130	.104	.118	.012
Model 2	.392		.036	.034	.034	.332	.008	.014	.006
N = 400									
Model 1	.898		.880	.886	.838	.784	.788	.788	.516
Model 2	.886		.038	.038	.038	.884	.020	.026	.024

Note. NH = Neighborhood; DP = Depression; PA = Parenting; EX = Externalizing.

Discussion

The present simulation results demonstrate that using the TJS to determine the significance of the indirect paths in the set of structural equation models examined here was clearly superior to using BC bootstrapping. Given the ease of use of the TJS (where, in essence, nothing above and beyond fitting the model is required), we believe that this is an important result for the average researcher using SEM.

With respect to the power to obtain significant indirect effects in Model 1 (and also for the single indirect effect not involving parenting in Model 2), we had expected at the outset to observe only that the TJS would perform comparably to BC bootstrapping. Hence, it came as somewhat of a surprise to us to see that the TJS approach actually performed better here than did BC bootstrapping.⁴ However, somewhat after the fact, we discovered that such results were foreshadowed by Mplus simulation results obtained by Thoemmes et al. (2010; involving observed variables and normal-theory Sobel tests of the indirect effects) who found that the tests for the individual component paths in three-path mediation models had much more power than the test for the overall indirect effect.

With respect to the attenuated Type I errors for the BC bootstrapping approach when fitting Model 2, such a result could be regarded as being inconsistent with the previous simulation work of MacKinnon et al. (2004), who found that BC bootstrapping seemed to do a good job on average of protecting Type I error (with all the other approaches serving to underestimate it). However, there was some evidence in MacKinnon et al. (2004) that when the population value of only one of the component paths in a two-path mediation model was 0 but the value of the other component path was large, BC bootstrapping resulted in slight inflations of the Type I error rate (see also Taylor et al., 2008, for analogous findings involving three-path mediation models, and Fritz, Taylor, & MacKinnon, 2013, for some additional recent work related to this issue). Because this situation is comparable to that in our Model 2 populations, we had expected to find a similar result here (but which ended up not actually being the case).

One limitation of the current study, however, is the number of population parameter by sample size conditions examined (i.e., only four; but, again, see Note 1). Moreover, two key assumptions about the underlying population values that were implicit in the simulations ran here are that they were both continuous and multivariate normally distributed (as opposed to categorical or nonnormal). As well, these simulations are relevant only to data that have been collected in a cross-sectional fashion and contains no missing values. Additionally, of course, is the fact that although the finding of a significant indirect effect (which we refer to as statistical mediation) is a necessary condition for concluding the presence of causal or substantive mediation, it is not a sufficient condition. Discussion of such sufficient conditions is beyond the scope of this current work, however, and is an issue that has been discussed in detail earlier (e.g., see MacKinnon et al., 2002).

Finally, one commonly cited limitation of the TJS approach is that it does not provide either point or interval estimates of the sizes of the indirect effects. Such estimates can be important because they provide key information regarding the strength

and precision of such effects (although note that a point estimate for an indirect effect can be obtained simply by multiplying the component path coefficients). As many behavioral researchers are quite aware, the reporting of confidence intervals for all experimental effects is a practice that is now highly recommended within the field (Wilkinson & the Task Force on Statistical Inference, 1999). Moreover, if an SEM researcher is specifically concerned with the sizes of any specific indirect effects, then indeed obtaining point estimates and confidence intervals for them would certainly be very appropriate (for methods to compare such effects with each other in multiple mediator models, see M. Cheung, 2007; Lau & Cheung, 2012; Preacher & Hayes, 2008). However, for such an approach to be useful in practice, it should be a fairly straightforward endeavor for anyone to be able to obtain such estimates, which, as we have discussed, is not always the case in SEM (especially for researchers using two of the most common SEM model-fitting programs; i.e., AMOS and LISREL).⁵ Hence, we would argue that if an SEM researcher is simply trying to test a hypothesized structural model of a phenomenon and, after fitting that model, would like to draw some statistical conclusions regarding the presence of indirect effects within that model, the simulation results reported here suggest that simple tests of joint significance are indeed likely to be sufficient for such purposes.

Appendix

MCDData150.inp

title: This is an example of a SEM with continuous factor indicators

montecarlo:

```
names = y1-y20;
nobs = 150;
nreps = 1;
seed = 59245;
save = mc1A150rep1.dat;
```

model montecarlo:

```
neigh by y6@1 y7*.9 y8*.8 y9*.7 y10*.6;
depress by y11@1 y12*.9 y13*.8 y14*.7 y15*.6;
parent by y16@1 y17*.9 y18*.8 y19*.7 y20*.6;
ext by y1@1 y2*.9 y3*.8 y4*.7 y5*.6;

y1-y20*1;

neigh*1;
depress-ext*1;

depress on neigh*.25;
parent on neigh*.25 depress*.25;
ext on neigh*.25 depress*.25 parent*.25;
```

model:

```
neigh by y6-y10;  
depress by y11-y15;  
parent by y16-y20;  
ext by y1-y5;  
  
depress on neigh;  
parent on neigh depress;  
ext on depress parent neigh;
```

MODEL INDIRECT:

```
ext IND depress neigh;  
ext IND parent neigh;  
ext IND parent depress;  
ext IND parent depress neigh;
```

MCAnalyze.inp

title: This is an example of a SEM with continuous factor indicators

DATA:

FILE IS "C:/Users/user/Documents/Mplus/NewFolder/mc1A150rep1.dat";

VARIABLE:

```
NAMES ARE y1-y20;  
USEVARIABLES ARE y1-y20;
```

ANALYSIS:

```
TYPE IS GENERAL;  
ESTIMATOR IS ML;  
ITERATIONS = 1000;  
CONVERGENCE = 0.00005;  
BOOTSTRAP = 1000;  
MODEL = NOMEANSTRUCTURE;  
INFORMATION = EXPECTED;
```

model:

```
neigh by y6-y10;  
depress by y11-y15;  
parent by y16-y20;  
ext by y1-y5;  
  
depress on neigh;  
parent on neigh depress;  
ext on neigh depress parent;
```

MODEL INDIRECT:

ext IND depress neigh;
ext IND parent neigh;
ext IND parent depress;
ext IND parent depress neigh;

OUTPUT:

cinterval(bcbootstrap) standardized Tech4;

Declaration of Conflicting Interests

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Notes

1. Note that given this constraint, it was just not feasible to examine very many population parameter by sample size combinations. Hence, the four conditions we chose to examine here seemed (to us) to be the most useful ones possible.
2. Note that the average root mean square error of approximation model fit values across the 500 simulated data sets for sample sizes of 150 were .018 and .020 for Models 1 and 2, respectively, and for sample sizes of 400 they were .008 and .008 for Models 1 and 2, respectively. Average standardized root mean square residual model fit values across the 500 simulated data sets for sample sizes of 150 were .056 and .053 for Models 1 and 2, respectively, and for sample sizes of 400 they were .034 and .032 for Models 1 and 2, respectively.
3. Note that the results in this table are based on the tests of the standardized specific indirect effects in Mplus (which seemed to be a bit more powerful than the tests of the unstandardized specific indirect effects).
4. Note that in some recent simulation work by Hayes and Scharkow (2014; involving the single, two-path mediator case with observed variables), BC bootstrapping did indeed seem to perform a bit better with respect to power than the TJS (which, nonetheless, performed second best). Moreover, it was also demonstrated that for the cases in which two methods disagreed (4% of the time), BC bootstrapping was more likely (83.3% vs. 16.7%) to identify the presence of an indirect effect than was the TJS. In our current simulation work, on the other hand, the opposite result held. Namely, it was never the case that BC bootstrapping uncovered a significant indirect effect that was not also uncovered by the TJS (whereas the reverse occurred numerous times). Although the reason for this inconsistency is not completely clear, it likely has something to do with differences in the nature of the simulation analyses examined in the current work (which involved complex latent variable models generated and analyzed in Mplus) in comparison to those examined by Hayes and Scharkow (2014).

5. Note that because of the comments of one of our reviewers, while revising this article we became aware of the fact that there is now a program for obtaining confidence intervals based on the distribution of products approach that is extremely easy to install and use (i.e., RMediation; Tofighi & MacKinnon, 2011). Namely, after downloading a free version of R, two lines of code will download, install, and load up the RMediation program. Manually entering path coefficient values and their standard errors (obtained directly from the model fit output provided by whatever SEM program is being used) into a third specified line of R code will immediately provide distribution of products confidence intervals (which also can all be done directly at <http://amp.gatech.edu/RMediation>). Moreover, a bit of supplemental work that we performed indicated that the power of this method might indeed be comparable to that of the TJS (i.e., both methods invariably seemed to yield the exact same conclusions regarding significance of the indirect effects present in the subset of simulation results that we reexamined). The only drawback of the distribution of products approach is that, so far, it can only be used to obtain confidence intervals for two-component indirect paths given the complexity involved in determining distributional solutions for compound paths with more than two components (although see a forthcoming article by D. Tofighi that reports on the implementation of a Monte Carlo method for obtaining confidence intervals for indirect paths with any number of components).

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