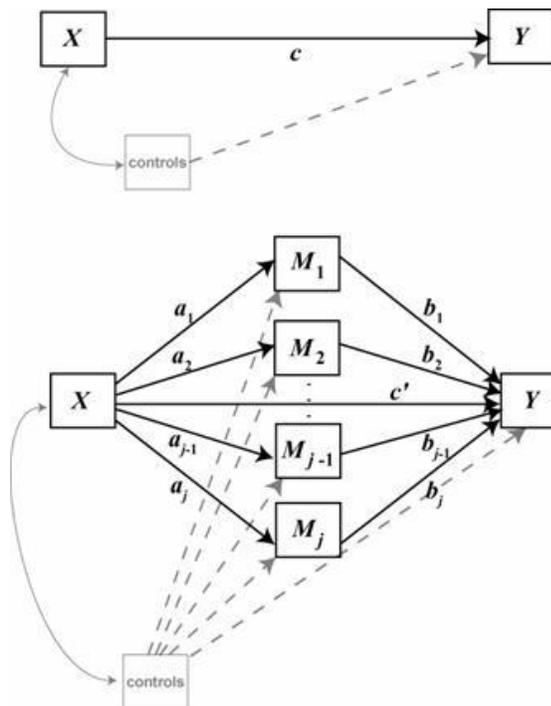


INDIRECT

```
%INDIRECT [DATA = datafile, Y = yvar, X = xvar, M = mvlist {covlist..}]  
    {,C = {cov} (0**) }  
    {,BOOT = {z} (1000**) }  
    {,CONF = {ci} (95**) }  
    {,NORMAL = {t} (0**) }  
    {,CONTRAST = {n} (0**) }  
    {,PERCENT = {p} (0**) }  
    {,BC = {b} (1**) }  
    {,BCA = {d} (0) };
```

Subcommands in braces are optional
** Default if subcommand is omitted



Overview

INDIRECT estimates the total, direct, and single-step indirect effects (specific and total) of causal variable `xvar` on outcome variable `yvar` through a proposed mediator variable or list of mediator variables `mvlist`, controlling for one or more variables listed in `covlist`. It calculates the Sobel test for the total and specific indirect effect(s) as well as percentile-based, bias-corrected, and bias-corrected and accelerated bootstrap confidence intervals for the indirect effects. When more than one variable is listed in `mvlist`, it also calculates normal theory and bootstrap tests of the difference between the indirect effects. For details on the methods, see Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling methods for estimating and comparing indirect effects. *Behavior Research Methods*, 40, 879-891. Estimates of all paths are calculated using OLS regression.

Examples

```
%INDIRECT (DATA = example, Y = know, X = educ, M = attn elab, CONTRAST = 1, NORMAL = 1, BOOT = 5000);
```

- Estimates the total and direct effects of `educ` on `know`, as well as the total and specific indirect effects of `educ` on `know` through `attn` and `elab`
- Produces the Sobel test for the total and specific indirect effects
- Conducts a contrast between the two specific indirect effects
- Generates 95% bias-corrected and accelerated bootstrap confidence intervals for the indirect effects using 5000 bootstrap samples.
- The analysis is conducted using a SAS data file named “example”

```
%INDIRECT (DATA = example, Y = know, X = educ, M = attn elab sex age educ, C = 3, CONTRAST = 1, CONF = 99, PERCENT = 1, BOOT = 1000);
```

- Estimates the total and direct effects of `educ` on `know`, as well as the indirect effect of `educ` on `know` through `attn` and `elab`, while controlling for `sex`, `age`, and `educ`
- Conducts a contrast between the two specific indirect effects
- Generates 99% percentile and bias-corrected and accelerated bootstrap confidence intervals for the indirect effects using 1000 bootstrap samples.

Covariates

The direct, indirect, and total effects of `xvar` on `yvar` can be calculated with or without including a set of covariates which are partialled out of `yvar` and any and all variables in the `m1ist` list. The covariates should be listed after the list of mediators in the `M =` subcommand, and then the number of covariates in `covlist` should be used as the argument for `COV` in the `C =` subcommand. For example, if four variables are provided in `covlist`, then specify `C = 4`. In the output, what is listed as the total effect of the independent variable is actually corrected for the effect of the covariates. To get an uncorrected total effect, remove the covariates from the model and rerun the macro.

The output will include a section labeled “Partial Effect of Control Variables on DV.” These are the partial regression weights for the covariates in the model of the outcome variable. `INDIRECT` does not provide the coefficients for the covariates in the model(s) of the mediator(s), although the covariates are in those models as well.

Normal Theory Tests and Contrasts

By setting `t` to 1 in the `NORMAL` subcommand, the macro conducts Sobel tests for the total and specific indirect effects, defined as the effect divided by its standard error. A *p*-value is derived using the standard normal distribution. If covariates are listed, the Sobel tests are not conducted or printed.

Specifying `n` equal to 1 in the `CONTRAST` subcommand produces pairwise contrasts between all specific indirect effects by calculating the difference, dividing it by its standard error, and deriving a *p*-value from the standard normal distribution. When there are only two mediator variables in the model, the contrast between specific indirect effects is listed in the output as `C1`. With *k* mediators, the $0.5k(k - 1)$ possible pairwise contrasts are listed as `C1`, `C2`, `C3`, and so forth, and a key for interpreting which code corresponds to which contrast is provided at the bottom of the output.

The standard errors for indirect effects and contrasts produced with the `/NORMAL` subcommand do *not* assume zero correlation between the errors in estimation of the proposed mediators.

Although the Sobel test is widely used in many fields, experts in mediation analysis discourage its use in favor of methods that respect the nonnormality of the sampling distribution of the indirect effect. See Preacher and Hayes (2008), Hayes (2009, 2018) or Hayes and Scharkow (2013), for a discussion.

Bootstrapping

By default, the macro generates 95% bias-corrected and accelerated bootstrap confidence intervals for all indirect effects and contrasts of indirect effects using $z = 1000$ bootstrap samples. The number of bootstrap samples can be changed by setting `z` in the `BOOT` subcommand to the desired number. The level of confidence for confidence intervals can be changed by setting `ci` to the desired number (such as 90, 99, and so forth) in the `CONF` subcommand. Percentile or bias-corrected confidence intervals can be requested by setting `p` and/or `b` to 1 in the `PERCENT` and/or `BC` subcommands, respectively. To turn off the printing of a particular form of bootstrap confidence interval, set its argument to 0 in the corresponding subcommand.

Multiple Independent Variables

In some cases the user might like to estimate a model that includes multiple independent variables each linked to the same set of mediators. The macro can be used to estimate the coefficients in such a model, although it provides no information that can be used to test a combined indirect effect involving all independent variables. Covariates are mathematically treated exactly like independent variables in the estimation, with paths to all mediators and the outcome, so if the desired model has k covariates, the macro can be run k times, each time listing one variable as the independent variable and the remaining $k - 1$ independent variables as covariates. Each run of the macro will generate the desired indirect effect for the variable currently listed as the independent variable.

A more efficient macro (`MEDIATE`) exists for estimation of direct and indirect effects in models with more than one independent variable. See Hayes and Preacher (in review).

Multicategorical Independent Variables

Hayes and Preacher (2014) discuss the estimation of direct and indirect effects of a multicategorical independent variable with more than levels using `MEDIATE` and `PROCESS`. `INDIRECT` is also capable of such an analysis using a procedure comparable to the one described for `PROCESS` in that paper. See Hayes and Preacher (2014) for details.

Notes

- `mvlist` and `yvar` must be quantitative variables and are assumed to have at least interval-level measurement properties. `xvar` and variables in `covlist` can be dichotomous or quantitative with interval-level properties. **INDIRECT should not be used with a dichotomous mediator.**
- When bootstrapping is enabled, the bootstrap samples are saved to a temporary SAS data file called “indirect”.

- A case will be deleted from the analysis if missing on any of the variables in the model.
- The macro is limited to the estimation of 10 specific indirect effects. If the user includes more than 10 mediators in the variable list, an error will result.
- All path coefficients in the output are unstandardized.

References

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: The Guilford Press.

Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology*, 67, 451-470.

Hayes, A. F. & Scharkow, M. (2013). The relative trustworthiness of tests of indirect effects in statistical mediation analysis: Does method really matter? *Psychological Science*, 24, 1918-1927.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs*, 76, 408-420.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40, 879-891.