SOBEL

```
SOBEL Y = yvar/X = xvar/M = mvar [/BOOT = {n}(0**)]
                                 [/EFFSIZE = {e}(0**)]
                                 [/VARORD = {v}(2**}]
                                 [/ITERATE = {i}{10000**}]
                                 [/CONVERGE = {cc}{.0000001**}].
```
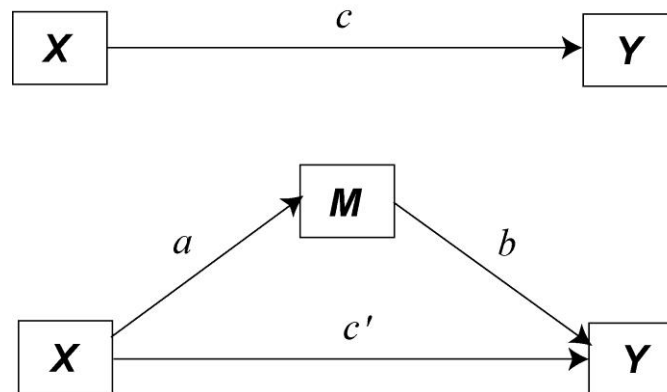
Subcommands in brackets are optional.
** Default if subcommand is omitted

Overview

SOBEL estimates the total, direct, and indirect effects of causal variable xvar on outcome variable yvar through a proposed mediator variable mvar. In also calculates the Sobel test for the indirect effect as well as a percentile-based bootstrap confidence interval for estimating the indirect effect, as described in Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, and Computers, 36*, 717-731. Since the publication of Preacher and Hayes (2004), the macro has been updated to allow for a binary outcome (*Y* only) and can also now use either a first or second order standard error estimator in the Sobel test.

Instructions for Use

The SOBEL.sps file should be opened as a syntax file in SPSS. Once it has been opened, execute the entire file exactly as is. Do not modify the code at all. Once the program is executed, the SOBEL program window can be closed. You then have access to the SOBEL command until you quit SPSS. See below for some example commands. The SOBEL.sps file must be loaded and reexecuted each time to open SPSS. To install SOBEL permanently in SPSS, install the custom dialog version (see below).

Example

```
SOBEL Y = know/X = educ/M = attn/BOOT = 5000/effsize = 1.
```

- Estimates the total and direct effects of educ on know, as well as the indirect effect of educ on know through attn
- Produces the Sobel test for the indirect effect using the second order standard error estimator.
- Generates a bootstrap confidence interval for the indirect effect using 5000 bootstrap samples.
- Produces effect size estimates for the indirect effect.

Bootstrapping

As discussed in Preacher and Hayes (2004, 2008), Hayes (2009, 2013) and Scharkow and Hayes (2013), bootstrap confidence intervals are preferred over the Sobel test because of the assumption the Sobel tests makes about the shape of the sampling distribution of the indirect effect. The `/BOOT` subcommand implements bootstrap estimation of a confidence intervals for the indirect effect. If it is not used, it defaults to 0 bootstrap resamples, meaning bootstrapping of the indirect effect is disabled. The user can enter the desired number of bootstrap samples as the argument for `n`, in intervals of 1000, for generating percentile-based bootstrap 95% and 99% confidence intervals. Only percentile-based bootstrap confidence intervals are estimated. For bias-corrected and accelerated confidence intervals, use the `INDIRECT` macro described in Preacher and Hayes (2008) or the `PROCESS` procedure (Hayes, 2013).

Because bootstrapping is based on random resampling of the data, bootstrap confidence intervals will differ slightly each time the macro is run as a result of the random sampling process. The more bootstrap samples that are requested, the less this variation between runs.

Standard Error Estimator in the Sobel Test

By default, `SOBEL` uses the second order standard error estimator in the Sobel test for the indirect effect. This standard error is defined as

$$se_{ab} = \sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}$$

The user can request the first order standard error estimator, defined as

$$se_{ab} = \sqrt{b^2 s_a^2 + a^2 s_b^2}$$

by setting `v` in the `/VARORD` subcommand to 1. If the `/VARORD` subcommand is not used, `v` defaults to 2 for the second order estimator.

Binary Outcome

By default, all paths in the model as estimated using OLS regression. But if `yvar` is binary, the *c*, *c'* and *b* paths are estimated using logistic regression. The coefficients the macro prints for b(YX), b(YX.M), and b(YM.X) are logistic regression coefficients, which estimate the effect of a one unit difference on the predictor on the log odds of the outcome. The macro automatically detects whether the outcome is binary and estimates the paths accordingly. The indirect effect is still estimated as the product of the *a* and *b* paths, and this product can be tested against the null of zero using the Sobel test or a bootstrap confidence interval, as in OLS.

In the event of nonconvergence during iteration toward the maximum likelihood solution for model coefficients, the macro allows the user to change the default number of iterations (`i`) and convergence criteria (`cc`) using the `/ITERATE` and `/CONVERGE` subcommands, which default to 10000 and .0000001, respectively. Iteration is accomplished using the Newton-Raphson method.

Note that unlike in OLS, when the binary is outcome, *ab* typically is not equal to *c* − *c'*. The coefficients and standard errors printed are not standardized, a method sometimes advocated for placing the direct,

indirect, and total effects on comparable scales. However, the macro will also print an estimate of the total effect that places it on the same scale as the indirect effect, using Formula 11.6 in MacKinnon (2008). This rescaled total effect then yields a difference between the total and direct effect that is much closer to (but still not the same as) the indirect effect. This rescaling does not affect the computation of the indirect effect or inferential tests.

Effect Size

By setting `e` to 1 in the `/effsize` subcommand (`i.e., /effsize = 1`), SOBEL generates 5 point estimates of the size of the indirect effect. The estimators, outlined in the table below, are discussed in Preacher and Kelley (2011).

Output	Formula
P_m	ab / c
R_m	ab / c'
R2_45	$r^2_{YM} - (R^2_{Y.MX} - r^2_{YX})$
ab_ps	ab / s_Y
ab_cs	$(s_X \, ab) / s_Y$

When used in conjunction with the bootstrapping option, percentile bootstrap 95% and 99% confidence interval estimates for these effect size measures are generated.

Multicategorical Independent Variables

For estimation of direct and indirect effects of a categorical IV with more than two levels, use MEDIATE (Hayes and Preacher, in review).

Nonlinear Effects

If you believe or have evidence that one or more of your effects is not well represented with a linear function, consider the use of MEDCURVE (Hayes & Preacher, 2010).

SOBEL Custom Dialog Box

If you use SOBEL frequently, you might find it convenient to install a version of the SOBEL macro into your SPSS menus. To do so, download the sobel_spss.spd (UI Dialog Builder) file from http://www.afhayes.com/ and double click on it. If you have administrative access to your machine, this should install a new option under your SPSS "Analyze→Regression" menu titled "Preacher and Hayes (2004) Simple Mediation Procedure (SOBEL)." You may have to run SPSS as administrator by right-clicking on the SPSS icon and selecting "Run as Administrator". If you do not have administrative access, you will have to contact your local information technology specialist for assistance in setting up administrative access to your computer.

PROCESS as a substitute for SOBEL

PROCESS is capable of everything SOBEL can do, but PROCESS has many more features not available in SOBEL. PROCESS is introduced in Hayes (2013) *An Introduction to mediation, moderation, and conditional process analysis* (http://www.guilford.com/p/hayes3).

Notes

- The proposed mediator variable, `mvar`, must be a quantitative variables and is assumed to have at least interval-level measurement properties. The independent variable, `xvar`, and outcome variable, `yvar`, can be quantitative with interval-level properties, or binary. **SOBEL should not be used with a dichotomous mediator.**

- Covariates are not allowed in `SOBEL`. If you'd like to control for the effect of variables outside the causal system on `mvar` and `yvar`, use the `INDIRECT` macro, as described in Preacher and Hayes (2008).

- When bootstrapping is enabled, the bootstrap samples are saved to an SPSS data file called "bootstrp.sav", typically in the SPSS root directory, although the exact location will vary from machine to machine depending on how the SPSS program was installed.

- A case will be deleted from the analysis if missing on any of the variables in the model.

- In the output, the following notation is used for the *a*, *b*, *c*, and *c′* paths in the diagram above: $a = b(MX)$; $b = b(YM.X)$; $c = b(YX)$; $c' = b(YX.M)$. All path coefficients are unstandardized.

- Do not use STRING formatted variables in any of your models. Doing so will produce errors. All variables should be NUMERIC format.

References

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: The Guilford Press.

Hayes, A. F. & Preacher, K. J. (2010). Estimating and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research, 45*, 627-660.

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.

MacKinnon, D. P. (2008). *An introduction to statistical mediation analysis.* Mahwah, NJ: Lawrence Erlbaum Associates.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, and Computers, 36*, 717-731.

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Preacher, K. J., & Kelley, K. (2011). Effect size measures for mediation models: Quantitative strategies for communicating indirect effects. *Psychological Methods, 16*, 93-115.