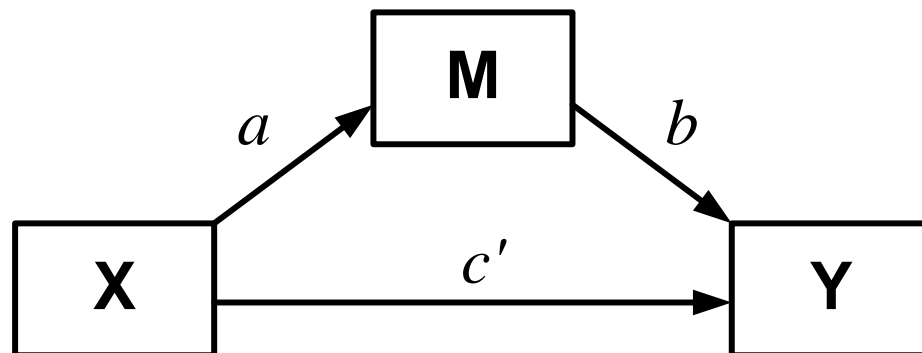


# MEDCURVE

```
MEDCURVE Y = yvar/X = xvar/M = mvar [cvarlist] [/aform = {a} (1**)]  
[/bform = {b} (1**)]  
[/cpform = {c} (1**)]  
[/xval = {xv}]  
[/percent = {p} (0**)]  
[/conf = {ci} (95**)]  
[/boot = {z} (0**)]  
[/save = {s} (0**)] .
```

Subcommands in brackets are optional

\*\* Default if subcommand is omitted



## Overview

MEDCURVE estimates instantaneous indirect effects of *xvar* (*X*) on *yvar* (*Y*) through *mvar* (*M*) while (optional) controlling for *cvarlist* in a simple mediation model, as discussed in Hayes and Preacher (in review). Unlike the SOBEL or INDIRECT macros introduced in Preacher and Hayes (2004, 2008), MEDCURVE does not impose the constraint that the paths between variables are linear in nature. The user can specify paths that are linear, logarithmic, exponential, quadratic, or inverse, in any combination, thereby producing 125 possible models. For inference, MEDCURVE generates bias corrected or percentile-based bootstrap confidence intervals for instantaneous indirect effects. When all paths are specified as linear, the standard indirect effect is calculated and inference available using either the Sobel test or bootstrapping. For theoretical details regarding instantaneous indirect effects, see Hayes, A. F., and Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research*, 45, 627-660.

## Preparing for Use

The MEDCURVE.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 MEDCURVE program window can be closed. You then have access to the MEDCURVE command until you quit SPSS. The MEDCURVE.sps file must be loaded and reexecuted each time SPSS is opened. See the “Examples” section below for some examples of how to set up a MEDCURVE command in a syntax window. Please also read the “Model Designation and Estimation” and “Notes” sections below for important details pertinent to execution.

## Examples

**MEDCURVE**  $Y = \text{know}/X = \text{educ}/M = \text{attn}/a\text{form} = 2/b\text{form} = 3/c\text{pform} = 1/\text{boot} = 2000.$

- Estimates the causal paths and instantaneous indirect effects for a model in which `educ` causally affects `know` through `attn`.
- The effect of `educ` on `attn` is modeled as logarithmic, the effect of `attn` on `know` controlling for `educ` is modeled as exponential, and the effect of `educ` on `know` controlling for `attn` is modeled as linear.
- Bootstrap standard errors and bias corrected bootstrap 95% confidence intervals for the instantaneous indirect effects are generated based on 2000 bootstrap samples.
- Instantaneous indirect effects are provided at the sample mean of `educ` as well as plus and minus one standard deviation below the sample mean.

**MEDCURVE**  $Y = \text{know}/X = \text{educ}/M = \text{attn } \text{sex } \text{age } \text{income}/a\text{form} = 4/b\text{form} = 1/c\text{form} = 2/\text{percent} = 1/\text{conf} = 99/\text{xval} = 3.5/\text{boot} = 5000.$

- Estimates the causal paths and instantaneous indirect effects for a model in which `educ` causally affects `know` through `attn`. Sex, age, and income are covariates and partialled out of all paths in the model.
- The effect of `educ` on `attn` is modeled as quadratic, the effect of `attn` on `know` controlling for `educ` (as well as sex, age, and income) is modeled as linear, and the effect of `educ` on `know` controlling for `attn` (as well as sex, age, and income) is modeled as logarithmic.
- Generates the bootstrap standard error and a 99% percentile-based bootstrap confidence interval for the instantaneous indirect effect when `educ` = 3.5, based on 5000 bootstrap samples.

## Specifying the Model

**MEDCURVE** estimates the coefficients pertinent to the model in the Figure on the prior page, using the least squares criterion. The functional forms of the *a*, *b*, and *c'* paths are specified using the `aform`, `bform`, and `cpform` subcommands and argument constants, respectively, according to the table below:

| Argument constant | Form of relationship between predictor and outcome |
|-------------------|--|
| 1                 | linear   |
| 2                 | logarithmic  |
| 3                 | exponential  |
| 4                 | quadratic  |
| 5                 | inverse  |

For instance, `/aform = 2` specifies a logarithmic relationship between *M* and *X*, `/bform = 4` specifies a quadratic relationship between *Y* and *M* holding *X* constant, and `/cpform = 3` specifies an exponential relationship between *X* and *Y* holding *M* constant. Thus, the string of subcommands `/aform = 2/bform = 4/cpform = 3` results in the estimation of the intercepts as well as *a*, *b*<sub>1</sub>, *b*<sub>2</sub>, and *c'* in the following models:

$$\hat{M} = i_1 + a \ln(X)$$

$$\hat{Y} = i_2 + b_1 M + b_2 M^2 + c' e^X$$

The table on the next page provides a few additional examples of combinations of `aform`, `bform`, and `cpform` and the resulting models of  $M$  and  $Y$  the combination produces. With five possible function forms and three paths, MEDCURVE can therefore estimate 125 different models.

MEDCURVE produces estimates of the intercepts and regression coefficients in its output, along with standard errors,  $t$ , and  $p$ -values for each coefficient. This information will coincide precisely with the coefficients generated in SPSS using its least squares regression procedure. Along with these coefficients, instantaneous indirect effects are generated using the procedure described in Hayes and Preacher (in review), listed in the output as “THETA”. The `aform`, `bform`, `cpform` arguments default to 1. Thus, when all three are left out of the MEDCURVE command, a standard linear simple mediation model is estimated, and the indirect effect is estimated as described in Preacher and Hayes (2004).

| Example sequence of arguments                | Corresponding path models  |
|--|--|
| <code>/aform = 2/bform = 1/cpform = 5</code> | $\hat{M} = i_1 + a \ln(X) ; \hat{Y} = i_2 + bM + c'(1/X)$                |
| <code>/aform = 3/bform = 4/cpform = 1</code> | $\hat{M} = i_1 + ae^X ; \hat{Y} = i_2 + b_1 M + b_2 M^2 + c'X$           |
| <code>/aform = 1/bform = 2/cpform = 3</code> | $\hat{M} = i_1 + aX ; \hat{Y} = i_2 + b \ln(M) + c'e^X$                  |
| <code>/aform = 5/bform = 3/cpform = 5</code> | $\hat{M} = i_1 + a(1/X) ; \hat{Y} = i_2 + be^M + c'(1/X)$                |
| <code>/aform = 4/bform = 2/cpform = 2</code> | $\hat{M} = i_1 + a_1 X + a_2 X^2 ; \hat{Y} = i_2 + b \ln(M) + c' \ln(X)$ |

Unless all paths are specified as linear or `xvar` is dichotomous, instantaneous indirect effects are generated by default at the sample mean of `xvar` as well as a standard deviation above and below the sample mean. If the user desires the instantaneous indirect effect at another value of `xvar`, this value can be specified as the argument in the (optional) `xval` subcommand. For instance, to generate the instantaneous indirect effect at the value of `xvar = 3`, include `/xval = 3` in the command line.

## Covariates

MEDCURVE provides the option of inclusion of variables in a model that serve as statistical controls. The list of covariates `cvarlist` identified in the command line following `mvar` will function as additional predictors in the model of `mvar` as well as in the model of `yvar`. Thus, all paths to `mvar` and `yvar` can be interpreted as partial effects, controlling for the variables in `cvarlist`. When estimating instantaneous indirect effects, all covariates are set to their sample means. See Hayes and Preacher (in review) for a discussion of interpretation.

## ***Bootstrapping for Inference***

Inference for instantaneous indirect effects are available only through bootstrapping, as described in Hayes and Preacher (in review). The number of bootstrap samples is specified as `z` in the `/boot` subcommand. For example, 5000 bootstrap samples are requested by adding `/boot = 5000` to the command line. MEDCURVE will generate a bootstrap confidence interval as well as the standard error of the instantaneous indirect effect, estimated as the standard deviation of the bootstrap estimates. The level of confidence is specified using the `/conf =` subcommand, using an argument between 50 and 99. For example, `/CONF = 99` specifies a 99 percent confidence intervals. Ninety five percent is the default. By default, bias corrected confidence intervals are produced when bootstrapping is enabled. To request percentile-based confidence intervals, use the `/PERCENT` subcommand, setting its argument to one (i.e., by adding `/PERCENT = 1` to the command line). Bootstrapping is disabled by default. If bootstrapping is not requested, only point estimates of instantaneous indirect effects is provided in the output.

If all paths are specified as linear, the same inferential options are available for the indirect effect through MEDCURVE as are available through SOBEL (Preacher and Hayes, 2004) and INDIRECT (Preacher and Hayes, 2008). In this case, a Sobel test for the indirect effect using the second-order standard error is provided. With bootstrapping enabled, the user can request percentile-based or bias corrected confidence intervals for the indirect effect as described above.

By setting `s` in the `/SAVE` subcommand to 1, the bootstrap estimates of the instantaneous indirect effect for each resample will be saved to a file named “MCEST.SAV.”

## ***MEDCURVE Custom Dialog Box***

If you use MEDCURVE frequently, you might find it convenient to install a version of the MEDCURVE macro into your SPSS menus. To do so, download the `medcurve.spd` (UI Dialog Builder) file from <http://www.afhayes.com/> and install by double clicking, right clicking, or open and install it from within SPSS under the Utilities menu. If you have administrative access to your machine, this should install a new option under your SPSS “Analyze→Regression” menu. 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.

Although the dialog box offers a “Paste” button, its use is not recommended. Users interested in embedding MEDCURVE commands in their own syntax should instead use the syntax driven macro rather than the custom dialog box for setting up the model.

The `xval` option is not available in the custom dialog version of MEDCURVE. To estimate the instantaneous indirect effect at specific values of `xvar`, use the macro in conjunction with the `xval` option.

## ***Notes***

- `mvar` and `yvar` must be a quantitative variables and are assumed to have at least interval-level measurement properties. `xvar` can be dichotomous or quantitative with interval-level properties.
- The macro has built in capacities for detecting models that are not mathematically permissible given the observed measurements. For example, if there are negative observations for a predictor

variable, then a logarithmic function cannot be specified for that variable. If such problems are detected, the macro will provide information to this effect in the output and will not estimate the model.

- Nonlinear models can sometimes produce problems with inversion of the matrix in SPSS's MATRIX language, which will lead to the SPSS error below. In such circumstances, try mean centering `xvar` and/or `mvar` and then reestimate the model.

```
Error encountered in source line # 19069
```

```
Error # 12417  
Source operand is singular for INV.  
This command not executed.
```

## References

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

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.

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.