%MEDCURVE

```
%MEDCURVE (data = datafile,Y = yvar,X = xvar,M = mvar [cvarlist]
                                          [,aform = {a}(1**)]
                                          [,bform = {b}(1**)]
                                          [,cpform = {c}(1**)]
                                          [,percent = {p}(0**)]
                                          [,conf = {ci}(95**)]
                                          [,boot = {z}(0**)]
                                          [,save = {s}(0**)]);
```
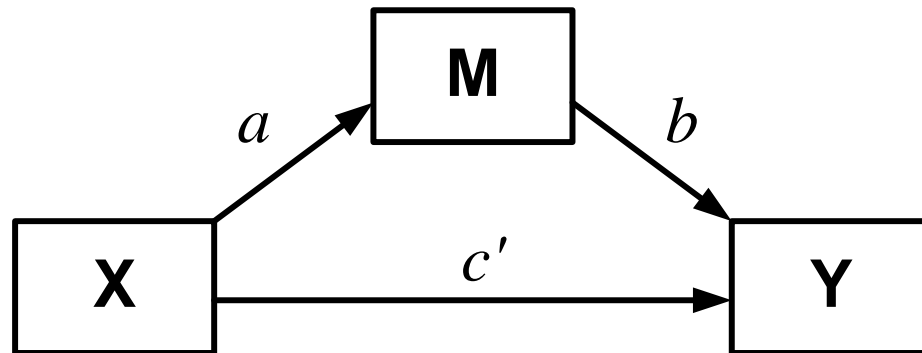
Subcommands in brackets are optional
** Default if subcommand is omitted

Overview

MEDCURVE estimates instantaneous indirect effects of xvar (*X*) on yvar (*Y*) through mvar (*M*) 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.

Examples

```
%MEDCURVE (data = immig, Y = know, X = educ, M = attn, aform = 2, bform = 3, cpform
   = 1, boot = 2000);
```

- Estimates the causal paths and instantaneous indirect effects for a model in which educ causally affects know through attn.   The SAS data file is named 'immig'.
- 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 (data =immig, Y = know, X = educ, M = attn, aform = 4, bform = 1, cform =
                  2, percent = 1, conf = 99, xval = 3.5, boot = 5000);
```

- 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 quadratic, the effect of `attn` on `know` controlling for `educ` is modeled as linear, and the effect of `educ` on `know` controlling for `attn` 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 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_1, b_2, 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 SAS using PROC REG. 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
`aform = 2, bform = 1, cpform = 5`	$\hat{M} = i_1 + a\ln(X); \hat{Y} = i_2 + bM + c'(1/X)$
`aform = 3, bform = 4, cpform = 1`	$\hat{M} = i_1 + ae^X; \hat{Y} = i_2 + b_1M + b_2M^2 + c'X$
`aform = 1, bform = 2, cpform = 3`	$\hat{M} = i_1 + aX; \hat{Y} = i_2 + b\ln(M) + c'e^X$
`aform = 5, bform = 3, cpform = 5`	$\hat{M} = i_1 + a(1/X); \hat{Y} = i_2 + be^M + c'(1/X)$
`aform = 4, bform = 2, cpform = 2`	$\hat{M} = i_1 + a_1X + a_2X^2; \hat{Y} = i_2 + b\ln(M) + c'\ln(X)$

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 SAS temporary data file named "mcest".

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.

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.