Testing Mediation with Regression Analysis Examples

SPSS

Below I use an SPSS macro developed by Kris Preacher and Andrew Hayes (2004) to test an indirect effect using the Yale social support data. In this example, age (AGE) is the predictor, social support (ISLSUM) is the mediator, and depression (HRS) is the final outcome. The "indirect" macro can be downloaded from: http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html

After downloading the macro, open it in a syntax window. Scroll down to the bottom of the macro syntax, and add the following lines (not case sensitive, but caps used here to denote commands):

```
INDIRECT Y = hrs /X = age /M = islsum /PERCENT=1.
EXECUTE.
```

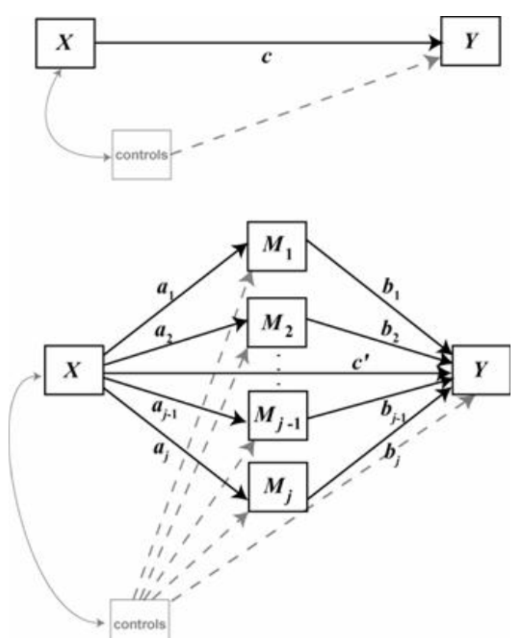
You will need to replace hrs, age, and islsum with your own variables. Y is the final outcome, X is the predictor, and M is the mediator. The /PERCENT=1 subcommand requests the confidence intervals that are not bias-corrected (i.e., standard percentile intervals).

Open your data set in the data window. Then, highlight the entire syntax in the syntax window, and run.

Output

The first section of the output (above the line of asterisks) gives each of the direct regression coefficients depicted in the diagram and will be the same as those you would obtain with the usual regression command in SPSS. The second section (below the line of asterisks) gives the bootstrap results. The "Data" column is the indirect effect calculated for the entire sample (no bootstrapping), the "Boot" column reports the average indirect effect for all of the bootstrap samples, and the "Bias" estimate is the degree to which this full sample estimate differs the bootstrap estimate, "SE" is the standard error, the "Bias Corrected and Accelerated Confidence Intervals" and the "Percentile Confidence Intervals" give the 95% confidence limits for all of the mediational effects ("Total", only one in this case) and for a particular mediator (just "islsum" in this case). When the confidence limits include 0, the indirect effect is nonsignificant. We will use the standard percentile confidence limits as the bias-corrected limits may have slightly elevated Type I error rates (Fritz, Taylor, & MacKinnon, 2012; Hayes & Scharkow, 2013)

```
Dependent, Independent, and Proposed Mediator
Variables:
DV =   hrs
IV =   age
MEDS = islsum

Sample size
        301

IV to Mediators (a paths)
           Coeff        se         t         p
islsum    -.0046     .0096    -.4800     .6316

Direct Effects of Mediators on DV (b paths)
           Coeff        se         t         p
islsum    -.7825     .1394   -5.6133     .0000

Total Effect of IV on DV (c path)
        Coeff        se         t         p
age    -.0552     .0244   -2.2629     .0244

Direct Effect of IV on DV (c' path)
        Coeff        se         t         p
age    -.0588     .0232   -2.5304     .0119
```



```
Model Summary for DV Model
      R-sq  Adj R-sq         F       df1       df2
p
     .1109     .1049   18.5762    2.0000  298.0000
.0000


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**********

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators
(ab paths)
            Data      Boot      Bias        SE
TOTAL      .0036     .0031    -.0006     .0080
islsum     .0036     .0031    -.0006     .0080

Bias Corrected Confidence Intervals
           Lower     Upper
TOTAL     -.0116     .0219
islsum    -.0116     .0219

Percentile Confidence Intervals
           Lower     Upper
TOTAL     -.0131     .0202
islsum    -.0131     .0202

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**********
Level of Confidence for Confidence Intervals:
  95

Number of Bootstrap Resamples:
  1000
```

R

```
#clear active frame from previous analyses
rm(mydata)


library(lessR)
mydata = Read("c:/jason/spsswin/da2/yale.sav",quiet=TRUE)

#install.packages("mediation")  #run before first use on a computer
library(mediation)

#listwise deletion necessary to make sample sizes for the two regressions match
mydata <-Subset(age!='NA' & islsum!='NA' & hrs!='NA')

#specify two separate models, one predicting the mediator, m, and one predicting the
outcome, y
# covariates can be included in either model
mmodel <-lm(islsum ~ age, data = mydata)
ymodel <- lm(hrs ~ islsum + age, data = mydata)

#request the boostrap indirect test, default is 1000 samples (usually ok),
#"perc" requests standard percentiles or use "bca" is for bias-corrected version
medtest <- mediate(mmodel, ymodel, treat = "age", mediator = "islsum", boot = TRUE,
boot.ci.type = "perc", data = mydata)
summary(medtest)
```

The output reports the "Estimate", which is the average indirect coefficient of the bootstrap samples, the 95% confidence intervals, and the p-value for significance test. The indirect coefficient is reported for the row labeled "ACME", which stands for average causal mediation effects, and the direct effect of x predicting y controlling for the mediator is labeled "ADE", which stands for average direct effect. The total effect is the two of these effects added together. The proportion mediated attempts to capture the portion of the total effect that is due to the mediation effect (details of the computations of this quantity vary).

```
Causal Mediation Analysis

Nonparametric Bootstrap Confidence Intervals with the Percentile Method

               Estimate 95% CI Lower 95% CI Upper p-value
ACME            0.00362     -0.01266      0.01871    0.65
ADE            -0.05879     -0.10995     -0.00865    0.02
Total Effect   -0.05517     -0.10742     -0.00484    0.03
Prop. Mediated -0.06560     -0.91788      0.31894    0.68

Sample Size Used: 301


Simulations: 1000
```

References

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

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. mediation: R Package for Causal Mediation Analysis. https://cran.r-project.org/web/packages/mediation/vignettes/mediation.pdf

Example Mediation Write-up

Sadly, my example above was not significant ☹, so I did another that would be ☺ for use in an example write-up. The output from the macro is included again here to see where the results came from. The example was an investigation of the hypothesis that therapy affects satisfaction by affecting attributional positivity.

Command added to end of macro:

```
INDIRECT y = satis /x = therapy /m = attrib  /percent = 1.
```

Output:

```
Dependent, Independent, and Proposed Mediator Variables:
DV =   satis
IV =   therapy
MEDS = attrib

Sample size
        30

IV to Mediators (a paths)
           Coeff        se         t         p
attrib     .8186     .2990    2.7375     .0106

Direct Effects of Mediators on DV (b paths)
           Coeff        se         t         p
attrib     .4039     .1808    2.2337     .0340

Total Effect of IV on DV (c path)
            Coeff        se         t         p
therapy     .7640     .3058    2.4984     .0186

Direct Effect of IV on DV (c' path)
            Coeff        se         t         p
therapy     .4334     .3221    1.3455     .1897

Model Summary for DV Model
      R-sq  Adj R-sq         F       df1       df2         p
     .3098     .2587    6.0605    2.0000   27.0000     .0067
*****************************************************************
           BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)
            Data      Boot      Bias        SE
TOTAL      .3306     .3145    -.0161     .1716
attrib     .3306     .3145    -.0161     .1716

Bias Corrected Confidence Intervals
           Lower     Upper
TOTAL      .0755     .7625
attrib     .0755     .7625

Percentile Confidence Intervals
           Lower     Upper
TOTAL      .0267     .7016
attrib     .0267     .7016
```

Regression analysis was used to investigate the hypothesis that social support mediates the effect of age on depression. Results indicated that therapy was a significant predictor of attributional positivity, b = .819, SE = .299, p < .05, and that attributional positivity was a significant predictor of satisfaction, b = .404, SE = .181 p < .05. These results support the mediational hypothesis. Therapy was no longer a significant predictor of satisfaction after controlling for the mediator, attributional positivity, b = .433, SE = .322, ns, consistent with full mediation. Approximately 31% of the variance in satisfaction was accounted for by the predictors (R^2 = .310). The indirect effect was tested using a bootstrap estimation approach with 1000 samples (Shrout & Bolger, 2002). These results indicated the indirect coefficient was significant, b = .331, SE = .314, 95% CI = .0267, .7016. Receiving therapy was associated with approximately .33 points higher satisfaction scores as mediated by attributional positivity.