

# Moderation, Mediation, & Conditional Indirect Effects

A Course in MplusAutomation

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## Outline

1. Estimate a moderation model with a continuous moderator
  2. Plot simple slopes with `ggplot` using data extracted from `.gh5` file produced by Mplus output
  3. Estimate a conditional mediation model with the `teams` data
- 

## Preparation

Install the `{rhdf5}` package to read `.gh5` files

```
if (!requireNamespace("BiocManager", quietly = TRUE))
  install.packages("BiocManager")
BiocManager::install("rhdf5")
```

```
library(tidyverse)
library(rhdf5)
library(MplusAutomation)
library(here)
library(gt)
library(gtsummary)
library(mediation)
library(carData)
library(plotly)
library(viridis)
```

## Upload list of `mplus.R` functions

<http://www.statmodel.com/mplus-R/mplus.R>

```
source(here("09-cond-mediation", "mplus.R.txt"))
```

```
## [1] "Loaded rhdf5 package"
```

## Data sources:

Models are adapted to demonstrate moderation and conditional mediation effects:

1. The first example utilize the *Vocabulary and Education* dataset from the National Opinion Research Center General Social Survey. GSS Cumulative Datafile 1972-2016 (Fox, 2008) [See documentation here](#)

To see metadata run - `?carData::Vocab`

2. The second example is from chapter 3 of the book, *Regression and mediation analysis using Mplus*, by Muthen et al., 2017. The dataset is called `teams` and is from a study about automobile parts work teams (Cole et al., 2008). This model is also discussed in the Hayes (2013) book on mediation.

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Read the `Vocab` data.frame into your R-environment from package `{carData}`

```
data(Vocab)

vocab <- Vocab %>%
  mutate(allyears = year - 1973)
```

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Starting with a familiar example but with moderator as continuous

Name	Labels
allyears (M)	Year of the survey (1974 - 2016)
education (X)	Students education in years
vocabulary (Y)	Vocabulary test score: number correct on a 10-word test

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## Model 1: Run moderation model with year (range: 1- 43) as a continuous moderator variable

```
m1_contmod <- mplusObject(
  TITLE = "m1 condition mediation (continuous moderator)",
  VARIABLE =
    "usevar =
      allyears education vocabulary int_yred; ",
  DEFINE =
    "!center education (grandmean);      ! leave un-centered for plot
    int_yred = allyears*education;      ! create interaction term ",
```

```

ANALYSIS =
  "estimator = MLR" ,

MODEL =
  "[vocabulary](b0);

  vocabulary on
  allyears(b1)
  education(b2)
  int_yred(b3); " ,

MODELCONSTRAINT =
  "LOOP(x,6.62,19.18,0.01);
  PLOT(y1974 y1984 y1995 y2005 y2016);
  y1974 = b0 + b1*1 + b2*x + b3*x*1;
  y1984 = b0 + b1*10 + b2*x + b3*x*10;
  y1995 = b0 + b1*21 + b2*x + b3*x*21;
  y2005 = b0 + b1*31 + b2*x + b3*x*31;
  y2016 = b0 + b1*42 + b2*x + b3*x*42; " ,

OUTPUT = "sampstat standardized modindices (3.84)",

PLOT = "type=plot3;",

usevariables = colnames(vocab),
rdata = vocab)

m1_contmod_fit <- mplusModeler(m1_contmod,
  dataout=here("09-cond-mediation", "mplus_files", "vocab.dat"),
  modelout=here("09-cond-mediation", "mplus_files", "m1_contmod.inp"),
  check=TRUE, run = TRUE, hashfilename = FALSE)

```

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## Plotting using data extracted from gh5 files produced by Mplus

1. View plots available for a given model
2. Generate plots using the `get.plot.---` function
3. Extract data and transform to tidy format
4. Plot with `ggplot`

```
mplus.view.plots(here("09-cond-mediation","mplus_files", "m1_contmod.gh5"))
```

```
mplus.plot.loop(here("09-cond-mediation","mplus_files", "m1_contmod.gh5"),label =3)
```

---

Prepare plot data

```

loop_data2 <- lapply(1:5, function(k) {

y_val <- mplus.get.loop.estimates(here("09-cond-mediation", "mplus_files", "m1_contmod.gh5"), label=k)
lower <- mplus.get.loop.lowerci(here("09-cond-mediation", "mplus_files", "m1_contmod.gh5"), label=k)
upper <- mplus.get.loop.upperci(here("09-cond-mediation", "mplus_files", "m1_contmod.gh5"), label=k)
x_val <- mplus.get.loop.xvalues(here("09-cond-mediation", "mplus_files", "m1_contmod.gh5"))

  loop_data2 <- as.data.frame(cbind(y_val, x_val, lower, upper)) %>%
    mutate(group = factor(k))

})

plot_data2 <- bind_rows(loop_data2)

```

Plot simple slopes moderation plot with standard error bands

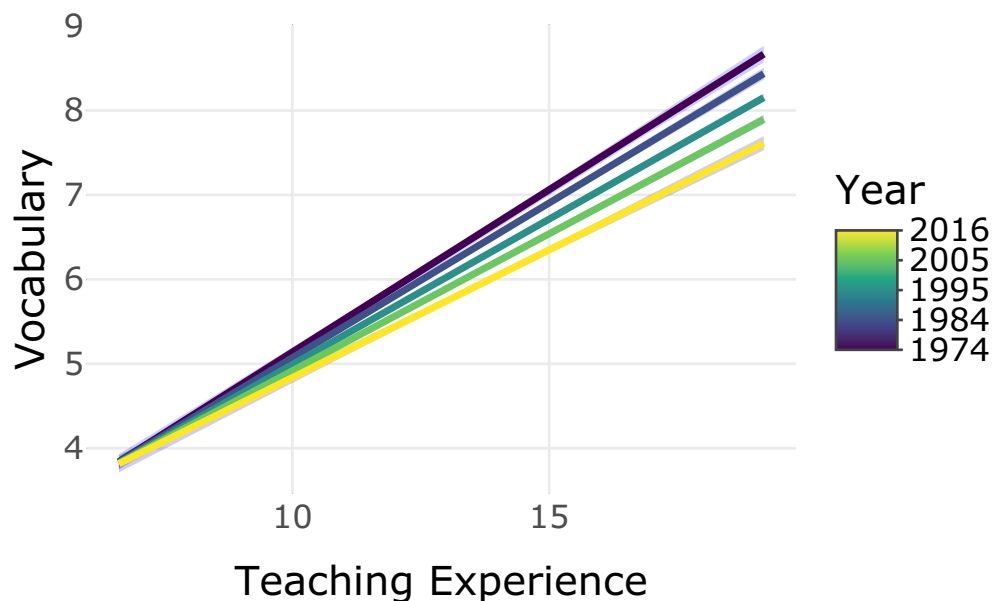
```

cont_plot <- ggplot(plot_data2, aes(x=x_val, y=y_val,
                                   group = group, color = as.numeric(group))) +
  geom_ribbon(aes(ymin = lower, ymax = upper),
            fill = "blue", alpha = .2, size = 0) +
  geom_line(size=.7) +
  scale_color_viridis_c(name = "Year", labels = c("1974", "1984", "1995", "2005", "2016")) +
  labs(y = "Vocabulary", x = "Teaching Experience") +
  theme_minimal()

```

Create interactive plot with ggplotly

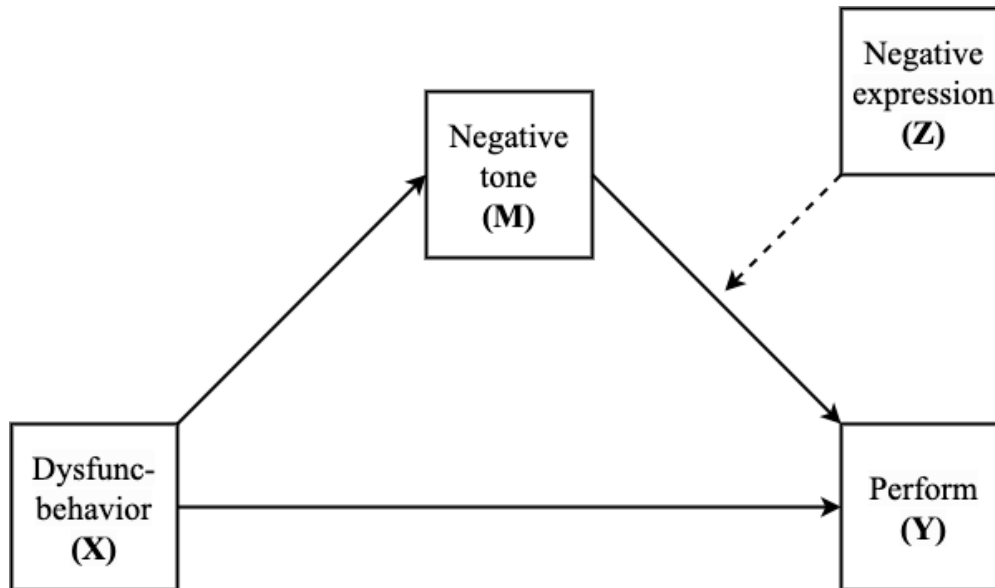
```
ggplotly(cont_plot)
```



## Mediation: Conditional indirect effect model

This version of moderated mediation is described as **case 2** in the Muthen et al. (2016) text.

Name	Labels
dysfunc (X)	Dysfunctional behavior of team members
negexp (Z)	Nonverbal negative expressibility between team members (measured by supervisor)
negtone (M)	Negative affective tone expressed by team members
perform (Y)	Team performance using measures of efficiency, timeliness, and objectives



Read in data

```
teams <- read_table(here("09-cond-mediation","data", "teams.txt"), col_names = FALSE)

colnames(teams) <- c("dysfunc", "negtone", "negexp", "perform")
```

## Model 2: Estimate conditional indirect effect model

```
m2_teams <- mplusObject(
  TITLE =
    "Data source - Hayes (2013) TEAMS Case 2 moderation of M -> Y ",
  VARIABLE =
    "usevar = dysfunc negtone negexp perform mz;",
  DEFINE =
    "MZ = negtone*negexp; ! create interaction term ",
  ANALYSIS =
    "! set number of bootstrap draws (small # for demonstration purposes)
    bootstrap = 500; " ,
```

```

MODEL =
  "perform on          !!! outcome (Y)
  negtone              !!! mediator (M)
  dysfunc              !!! covariate (X)
  negexp               !!! moderator (Z)
  mz;                  !!! interaction (MZ)

  negtone on dysfunc;  !!! path X -> M

  Model indirect:
  perform MOD
  negtone negexp(-0.4,0.6,0.1) mz dysfunc(0.4038 0.035); ",

OUTPUT =
  "sampstat standardized cinterval (bcbootstrap); ! bias-corrected bootstrap",

PLOT = "type=plot3;",

usevariables = colnames(teams),
rdata = teams)

m2_teams_fit <- mplusModeler(m2_teams,
  dataout=here("09-cond-mediation", "mplus_files", "teams.dat"),
  modelout=here("09-cond-mediation", "mplus_files", "m2_teams.inp"),
  check=TRUE, run = TRUE, hashfilename = FALSE)

```

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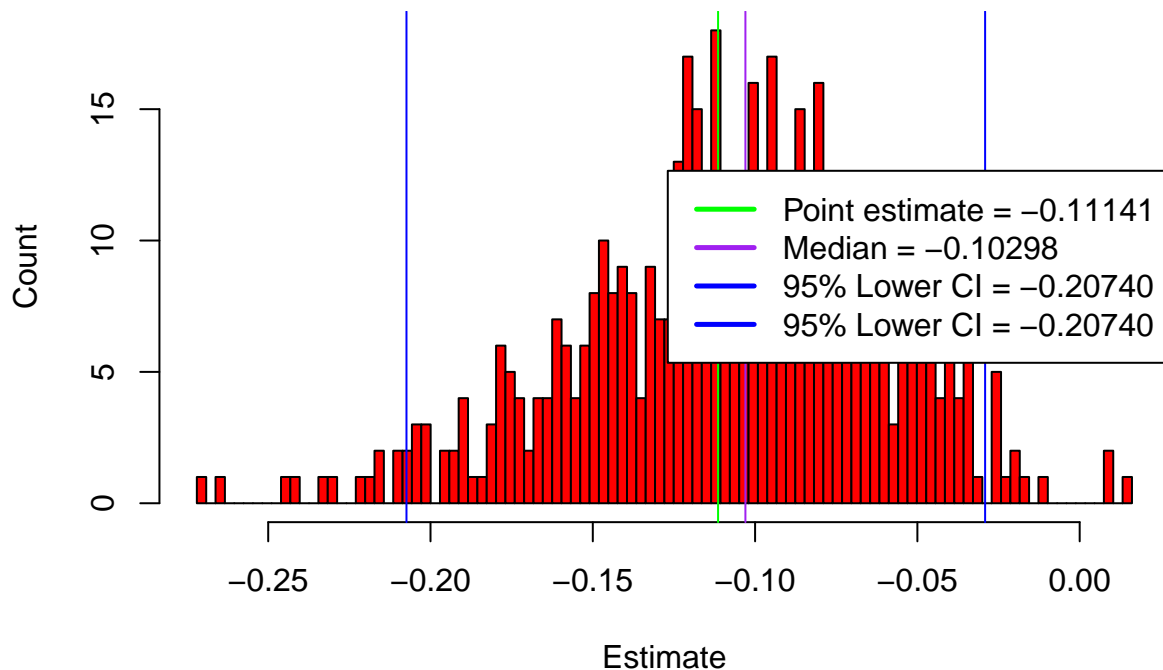
Take a look at bootstrap distribution of the indirect effect to view asymptotic shape.

```

mplus.plot.bootstrap.distribution(here("09-cond-mediation", "mplus_files", "m2_teams.gh5"), parameter =

```

## bootstrap distribution of: DYSFUNC to PERFORM for NEGEXP = 0.100: Pure



To see animation of how the bootstrap distribution changes with increasing sample draws (N) go here:  
[https://raw.githubusercontent.com/minimaxir/frames-to-gif-osx/master/examples/uni\\_frames.gif](https://raw.githubusercontent.com/minimaxir/frames-to-gif-osx/master/examples/uni_frames.gif)

Create plot of moderated direct and indirect effects

```
label <- c('Total natural DE', 'Total natural IE')

mod_data <- lapply(1:2, function(k) {
  y_val <- mplus.get.moderation.estimates(here("09-cond-mediation", "mplus_files", "m2_teams.gh5"), label)
  lower <- mplus.get.moderation.lowerci(here("09-cond-mediation", "mplus_files", "m2_teams.gh5"), label)
  upper <- mplus.get.moderation.upperci(here("09-cond-mediation", "mplus_files", "m2_teams.gh5"), label)
  x_val <- mplus.get.moderation.xvalues(here("09-cond-mediation", "mplus_files", "m2_teams.gh5"))

  mod_data <- as.data.frame(cbind(y_val, x_val, lower, upper)) %>%
    mutate(group = factor(k))
})

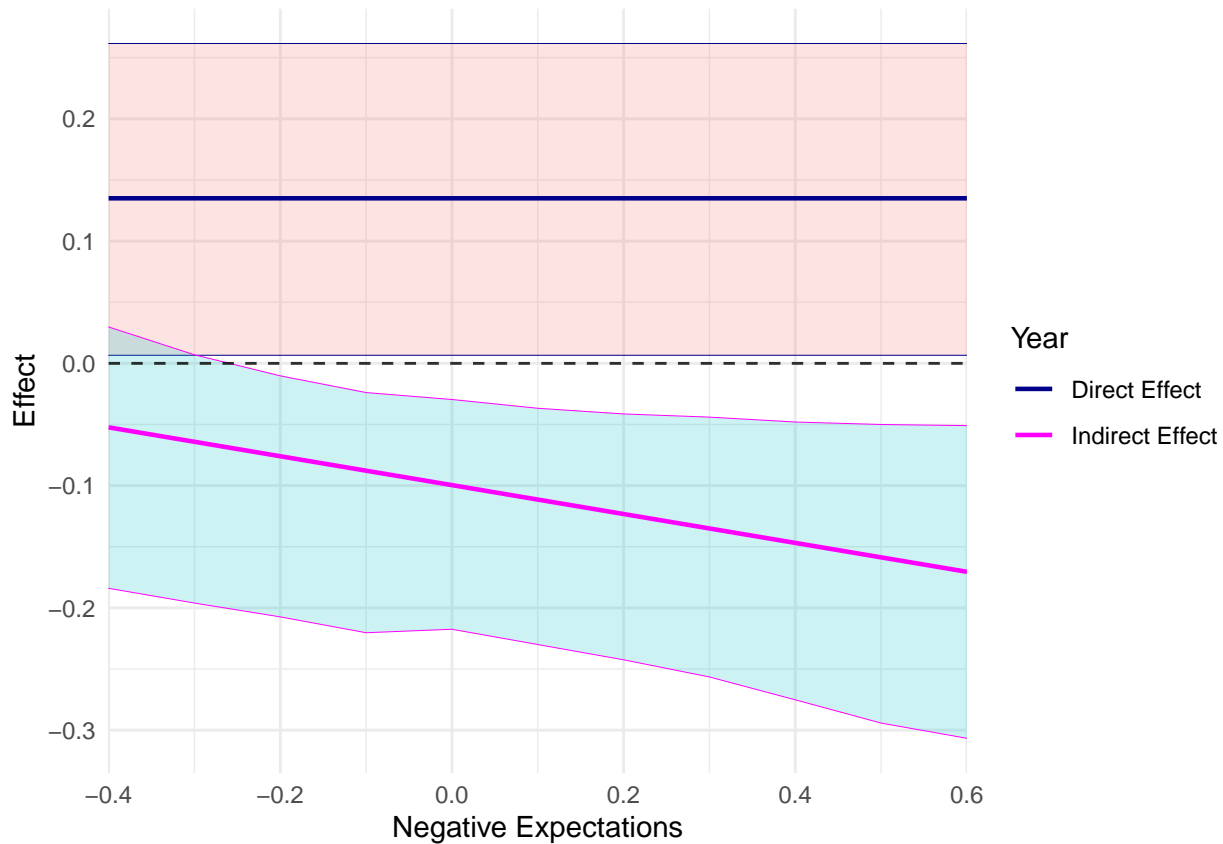
plot_data2 <- bind_rows(mod_data)

ggplot(plot_data2, aes(x=x_val, y=y_val,
                      group = group, color = group, fill = group)) +
  geom_ribbon(aes(ymin = lower, ymax = upper),
```

```

    alpha = .2, size = 0, show.legend = FALSE) +
  geom_line(size=.8) +
  geom_hline(yintercept = 0, alpha =.8, linetype = 2) +
  scale_x_continuous(expand = c(0,0)) +
  scale_color_manual(values=c("darkblue", "magenta"),
    name = "Year", labels = c("Direct Effect", "Indirect Effect")) +
  labs(y = "Effect" , x = "Negative Expectations") +
  theme_minimal()

```



## References

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- Ingels, S. J., Pratt, D. J., Herget, D. R., Burns, L. J., Dever, J. A., Ottem, R., ... & Leinwand, S. (2011). High School Longitudinal Study of 2009 (HSLs: 09): Base-Year Data File Documentation. NCES 2011-328. National Center for Education Statistics.
- Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2017). Regression and mediation analysis using Mplus. Los Angeles, CA: Muthén & Muthén.



Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis.

Vinokur AD, Price RH, Schul Y (1995). Impact of the JOBS Intervention on Unemployed Workers Varying in Risk for Depression. *American Journal of Community Psychology*, 23(1), 39–74.

Wickham et al., (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686, <https://doi.org/10.21105/joss.01686>

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### **Further resources & examples here:**

<https://garberadamc.github.io/project-site/>

<https://www.adam-garber.com/>

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