Lab 5 - Conditional Indirect Effects

Structural Equation Modeling ED 216F - Instructor: Karen Nylund-Gibson

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Contents

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1 Lab preparation

1.1 Creating a version-controlled R-Project with Github

Download repository here: https://github.com/garberadamc/SEM-Lab4

On the Github repository webpage:

a. `fork` your own `branch` of the lab repository
b. copy the repository web URL address from the `clone or download` menu

Within R-Studio:

c. click "NEW PROJECT" (upper right corner of window)
d. choose option `Version Control`
e. choose option `Git`
f. paste the repository web URL path copied from the `clone or download` menu on Github page
g. choose location of the R-Project (too many nested folders will result in filepath error)

1.2 Load packages

```
install.packages("hrbrthemes", repos = "https://cinc.rud.is")
```

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

1.3 Upload list of `mplus.R` functions

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

```
source(here("mplus.R.txt"))
```

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

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2 Lab outline

1. Run a simple moderation model with binary moderator (re-coded)
2. Plot simple slopes with `ggplot` using data extracted from `gh5` file produced by Mplus output
3. Run a parallel model with interaction between two continuous variables
4. Estimate a conditional mediation model with the `teams` data

2.1 Data sources:

Models are adapted to demonstrate moderation and conditional mediation effects:

1. The first two examples 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`

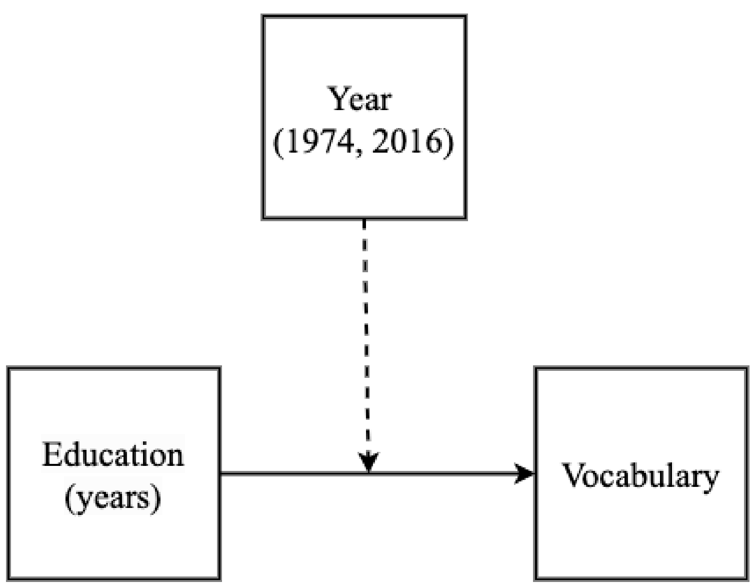
2. The third example is from chapter 3 of the book, *Regression and mediation analysis using Mplus*, by Muthen et al., 2017. The dataset is called `teams` and is from a study about automobile parts work teams (Cole et al., 2008). This model is also discussed in the Hayes (2013) book on mediation.

Read the `Vocab` dataframe into your R-environment from package {`carData`}

```
data(Vocab)

vocab <- as.data.frame(Vocab) %>% mutate(year_new = year - 1973)

vocab2 <- vocab %>% filter(year %in% c(1974, 2016)) %>% mutate(year = droplevels(factor(year)))
```

Starting with a familiar example

Name	Labels
year	Year of the survey (1974 - 2016)
sex	Sex of the respondent (Female or Male)
education	Students education in years
vocabulary	Vocabulary test score: number correct on a 10-word test



$$\text{vocabulary} = \alpha + \beta_1(\text{year}) + \beta_2(\text{education}) + \beta_3(\text{year} \times \text{education}) + \epsilon$$

2.2 Model 1: Run moderation with binary moderator variable year

```
m1_lev2mod  <- mplusObject(
  TITLE = "m5 model indirect - Lab 3",
  VARIABLE =
    "usevar =
    year education vocabulary int_yred; ",

  DEFINE =
    "!center education (grandmean); ! leave un-centered for plot
     int_yred = year*education;     ! create interaction term ",

  ANALYSIS =
    "estimator = MLR" ,

  MODEL =
   "[vocabulary](b0);
    vocabulary on
    year(b1)
    education(b2)
    int_yred(b3); " ,

  MODELCONSTRAINT =
  "LOOP(x,6.62,19.18,0.01); ! 2SD above/below mean
   PLOT(y1974 y2016);
   y1974 = b0 + b2*x;
   y2016 = b0 + b1 + (b2+b3)*x;

   new(hi_y1974 lo_y1974 hi_y2016 lo_y2016 diff_hi);
   hi_y1974 = b0 + b2*(6.28);
   lo_y1974 = b0 + b2*(-6.28);
   hi_y2016 = b0 + b1 + (b2 + b3)*(6.28);
   lo_y2016 = b0 + b1 + (b2 + b3)*(-6.28);
    diff_hi = hi_y2016 - hi_y1974; ",

  OUTPUT = "sampstat standardized modindices (3.84)",

  PLOT = "type=plot3;",

  usevariables = colnames(vocab2),
  rdata = vocab2)

m1_lev2mod_fit <- mplusModeler(m1_lev2mod,
                     dataout=here("mplus_files", "Lab5.dat"),
                     modelout=here("mplus_files", "m1_lev2mod_Lab5.inp"),
                     check=TRUE, run = TRUE, hashfilename = FALSE)
```

2.3 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("mplus_files", "m1_lev2mod_Lab5.gh5"))
```

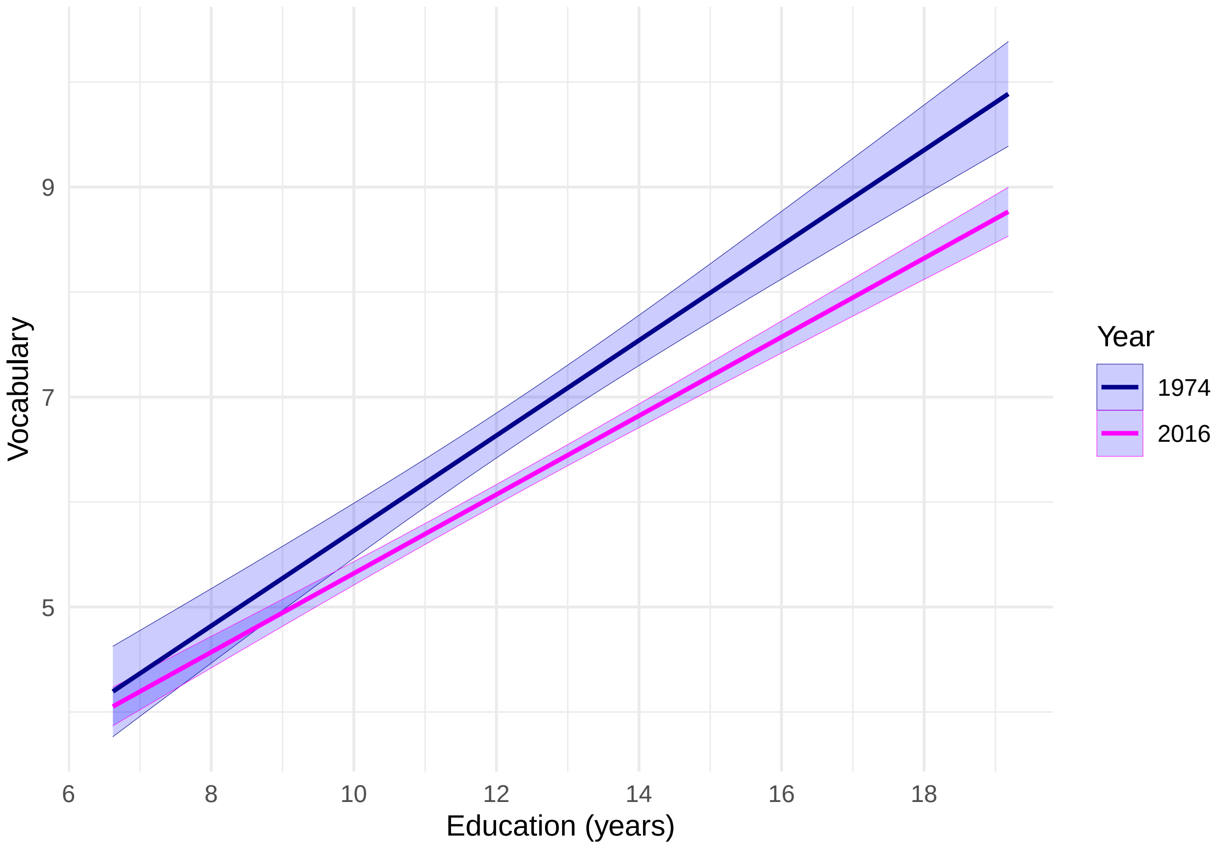
```
mplus.plot.loop(here("mplus_files", "m1_lev2mod_Lab5.gh5"), label = 1)
```

Prepare plot data -

```
loop_data <- lapply(1:2, function(k) {
    y_val <- mplus.get.loop.estimates(here("mplus_files", "m1_lev2mod_Lab5.gh5"),
        label = k)
    lower <- mplus.get.loop.lowerci(here("mplus_files", "m1_lev2mod_Lab5.gh5"), label = k)
    upper <- mplus.get.loop.upperci(here("mplus_files", "m1_lev2mod_Lab5.gh5"), label = k)
    x_val <- mplus.get.loop.xvalues(here("mplus_files", "m1_lev2mod_Lab5.gh5"))

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

})

plot_data <- bind_rows(loop_data)
```

Plot simple slopes moderation with standard error ribbons

```
ggplot(plot_data, aes(x = x_val, y = y_val, group = group, color = group)) + geom_ribbon(aes(ymin = lowe
    ymax = upper), fill = "blue", alpha = 0.2, size = 0) + geom_line(size = 0.8) +
    scale_color_manual(values = c("darkblue", "magenta"), name = "Year", labels = c("1974",
        "2016")) + scale_x_continuous(breaks = c(seq(6, 20, 2))) + labs(y = "Vocabulary",
    x = "Education (years)") + theme_minimal()
```



2.4 Model 2: Run moderation with continuous moderator variable `year` (range: 1- 42)

```
m2_contmod  <- mplusObject(
  TITLE = "m5 model indirect - Lab 3",
  VARIABLE =
    "usevar =
     year_new education vocabulary int_yred; ",

  DEFINE =
    "!center education (grandmean);     ! leave un-centered for plot
     int_yred = year_new*education;     ! create interaction term ",

  ANALYSIS =
    "estimator = MLR" ,

  MODEL =
   "[vocabulary](b0);
    vocabulary on
    year_new(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)

m2_contmod_fit <- mplusModeler(m2_contmod,
                              dataout=here("mplus_files", "Lab5.dat"),
                              modelout=here("mplus_files", "m2_contmod_Lab5.inp"),
                              check=TRUE, run = TRUE, hashfilename = FALSE)
```

Prepare plot data

```
loop_data2 <- lapply(1:5, function(k) {
    y_val <- mplus.get.loop.estimates(here("mplus_files", "m2_contmod_Lab5.gh5"),
        label = k)
    lower <- mplus.get.loop.lowerci(here("mplus_files", "m2_contmod_Lab5.gh5"), label = k)
    upper <- mplus.get.loop.upperci(here("mplus_files", "m2_contmod_Lab5.gh5"), label = k)
    x_val <- mplus.get.loop.xvalues(here("mplus_files", "m2_contmod_Lab5.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 = 0.2, size = 0) +
    geom_line(size = 0.7) + scale_color_viridis_c(name = "Year", labels = c("1974",
    "1984", "1995", "2005", "2016")) + labs(y = "Vocabulary", x = "Education (years)") +
    theme_ipsum()
```

Create interactive plot with `ggplotly`

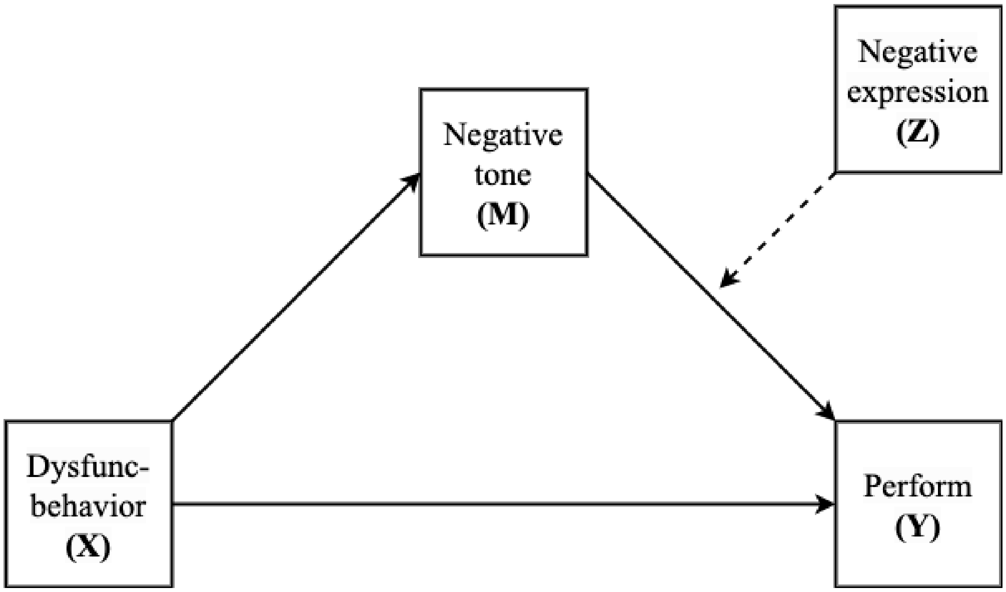
```
ggplotly(cont_plot)
```

Year

2.5 Conditional indirect effect model

This version of 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("data", "teams.txt"), col_names = FALSE)

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

2.6 Model 3: Estimate conditional indirect effect model

```
m3_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 negtone dysfunc negexp mz;
    negtone on dysfunc;

    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)

m3_teams_fit <- mplusModeler(m3_teams,
                    dataout=here("mplus_files", "Lab5.dat"),
                   modelout=here("mplus_files", "m3_teams_Lab5.inp"),
                   check=TRUE, run = TRUE, hashfilename = FALSE)
```

Model 3 Mplus output

TOTAL, INDIRECT, AND DIRECT EFFECTS BASED ON COUNTERFACTUALS (CAUSALLY-DEFINED EFFECTS)

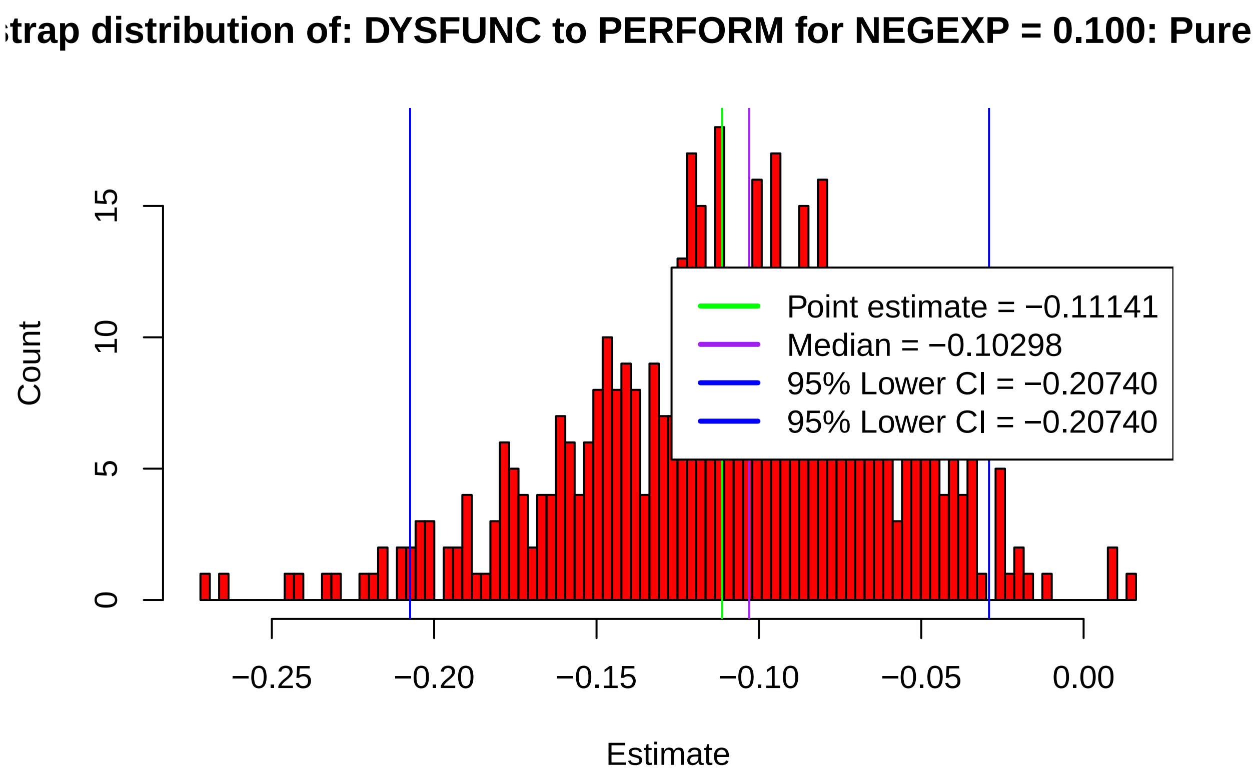
```
    Effects from DYSFUNC to PERFORM for NEGEXP = -0.100

      Tot natural IE      -0.088      0.045     -1.939      0.052
      Pure natural DE      0.135      0.069      1.962      0.050
      Total effect         0.047      0.071      0.664      0.507

    Effects from DYSFUNC to PERFORM for NEGEXP = 0.000

      Tot natural IE      -0.100      0.045     -2.194      0.028
      Pure natural DE      0.135      0.069      1.962      0.050
      Total effect         0.035      0.073      0.488      0.626

    Effects from DYSFUNC to PERFORM for NEGEXP = 0.100

      Tot natural IE      -0.111      0.047     -2.391      0.017
      Pure natural DE      0.135      0.069      1.962      0.050
      Total effect         0.024      0.075      0.316      0.752
```

View available plots from the `Mplus` model

```
mplus.view.plots(here("mplus_files", "m3_teams_Lab5.gh5"))
```

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

```
mplus.plot.bootstrap.distribution(here("mplus_files", "m3_teams_Lab5.gh5"), parameter = 38)
```



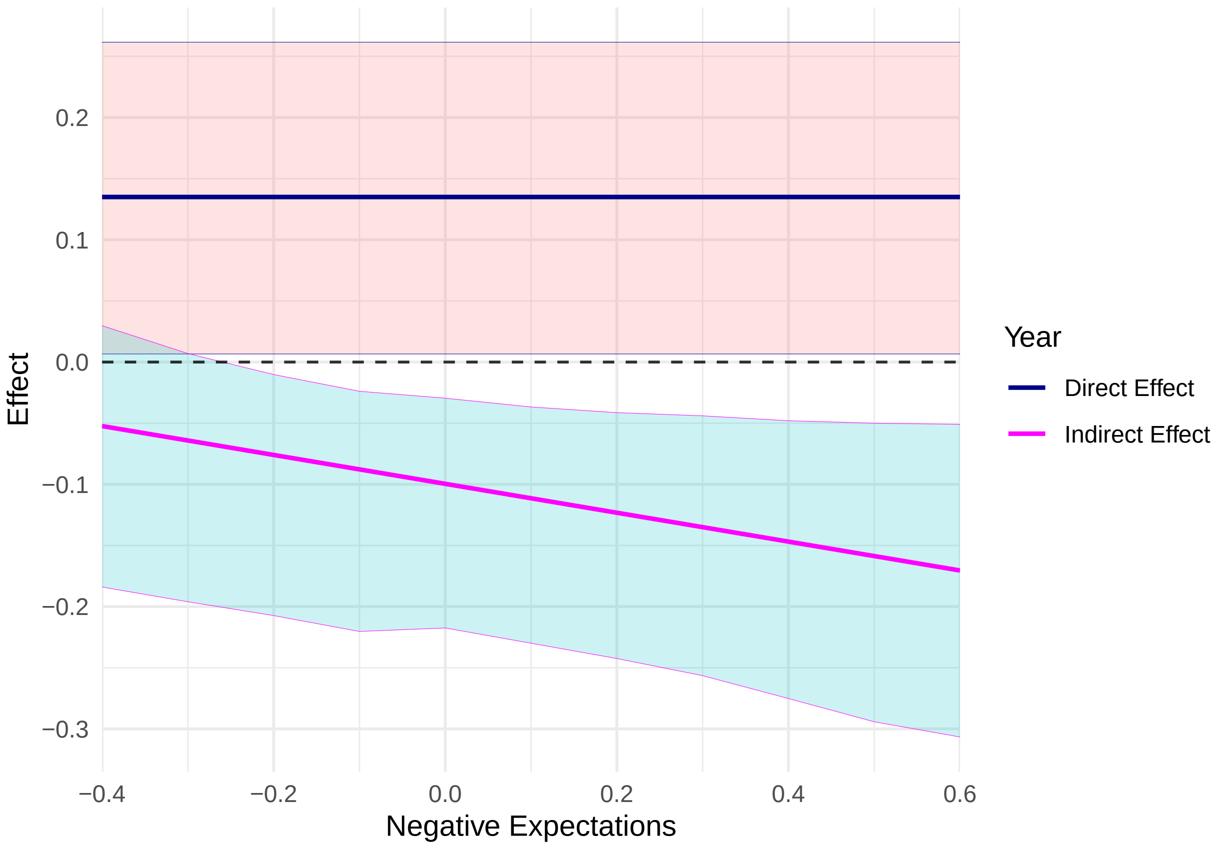
To see animation of how the bootsrap distribution changes with increasing sample draws (N) go here: https://raw.githubusercontent.com/minimaxir/frames-to-gif-osx/master/examples/uni_frames.gif

---

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("mplus_files", "m3_teams_Lab5.gh5"),
        label[k])
    lower <- mplus.get.moderation.lowerci(here("mplus_files", "m3_teams_Lab5.gh5"),
        label[k])
    upper <- mplus.get.moderation.upperci(here("mplus_files", "m3_teams_Lab5.gh5"),
        label[k])
    x_val <- mplus.get.moderation.xvalues(here("mplus_files", "m3_teams_Lab5.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 = 0.2, size = 0, show.legend = FALSE) +
    geom_line(size = 0.8) + geom_hline(yintercept = 0, alpha = 0.8, 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()
```



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3 References

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