Load necessary packages

```
library(tidyverse)
library(data.table)
library(reshape2)
library(ggpubr)
library(lmerTest)
library(reghelper)
library(sjstats)
library(sjPlot)
library(gridExtra)
library(stargazer)
library(lavaan)
library(semPlot)
library(psych)
theme_set(theme_classic(base_size = 14))
source('C:/Users/Cole/Documents/GitHub/PLIC/Process-Merge-Concat/PLIC_DataProcessing.R')
```

Read and match

```
full.df <- fread('C:/Users/Cole/Documents/PLIC_DATA/Collective_Surveys/Complete/Complete_Concat.csv') %>
  Merge.CIS(., Matched = TRUE) %>%
  filter(Survey_x == 'C' | Survey_y == 'C') %>%
  mutate(Lab_Level = case_when(
    Lab_Level == 'Intro-Algebra' ~ 'FY.Alg',
    Lab_Level == 'Intro-Calculus' ~ 'FY.Calc',
    (Lab_Level == 'Sophomore') | (Lab_Level == 'Junior') | (Lab_Level == 'Senior') ~ 'BFY',
    TRUE ~ NA_character_
  ),
  Lab_Purpose = case_when(
    Lab_Purpose == 'Both about equally' ~ 'Both',
    Lab_Purpose == 'Develop lab skills' ~ 'Skills',
    Lab_Purpose == 'Reinforce physics concepts' ~ 'Concepts',
    TRUE ~ NA_character_
  ))

print('Total # of students in dataset...')
```

```
## [1] "Total # of students in dataset..."
```

```
nrow(full.df)
```

```
## [1] 10888
```

```
print('Total # of classes in dataset...')
```

```
## [1] "Total # of classes in dataset..."
```

```r
length(unique(full.df$Class_ID))
```

```
## [1] 119
```

```r
print('Total # of institutions in dataset..')
```

```
## [1] "Total # of institutions in dataset.."
```

```r
length(unique(full.df$School))
```

```
## [1] 47
```

```r
# Remove whole classes without goal and/or level information or that were only administered at pre or p
full.df <- data.table(full.df)[, `:=`(N.students = .N, pre.rate = sum(Survey_x == 'C')/.N,
                                       post.rate = sum(Survey_y == 'C')/.N),  .(Class_ID)]

full.df <- full.df %>%
  filter(!is.na(Lab_Level) & !is.na(Lab_Purpose) & (pre.rate > 0) & (post.rate > 0))

print('# of remaining students in full dataset...')
```

```
## [1] "# of remaining students in full dataset..."
```

```r
nrow(full.df)
```

```
## [1] 8821
```

```r
print('# of remaining classes in full dataset...')
```

```
## [1] "# of remaining classes in full dataset..."
```

```r
length(unique(full.df$Class_ID))
```

```
## [1] 87
```

```r
print('Total # of institutions in dataset..')
```

```
## [1] "Total # of institutions in dataset.."
```

```r
length(unique(full.df$School))
```

```
## [1] 35
```

```r
df.matched <- full.df %>%
  filter(!is.na(PreScores) & !is.na(PostScores))

print('# of students in matched dataset...')
```

```
## [1] "# of students in matched dataset..."
```

```r
nrow(df.matched)
```

```
## [1] 5018
```

```r
print('# of classes in matched dataset...')
```

```
## [1] "# of classes in matched dataset..."
```

```r
length(unique(df.matched$Class_ID))
```

```
## [1] 87
```

```r
print('Total # of institutions in dataset..')
```

```
## [1] "Total # of institutions in dataset.."
```

```r
length(unique(df.matched$School))
```

```
## [1] 35
```

```r
table(df.matched[!duplicated(df.matched$School),]$Institution_Type, exclude = NULL)
```

```
##
##                  4 year college Master's granting institution
##                              14                             2
##       PhD granting institution
##                              19
```

```r
table(df.matched[!duplicated(df.matched$Class_ID),]$Lab_Level, exclude = NULL)
```

```
##
##     BFY  FY.Alg FY.Calc
##      27       9      51
```

```r
table(df.matched[!duplicated(df.matched$Class_ID),]$Lab_Purpose, exclude = NULL)
```

```
##
##     Both Concepts   Skills
##       25       18       44
```

```r
colSums(df.matched[, c('Q6f_1_y', 'Q6f_3_y', 'Q6f_5_y', 'Q6f_7_y')], na.rm = TRUE)
```

```
## Q6f_1_y Q6f_3_y Q6f_5_y Q6f_7_y
##      48     214      26      97
```

Data processing

```
df.matched <- df.matched %>%
  mutate(Major = case_when(
    (Q6b_y == 1) | (Q6b_y == 2) | (Q6b_y == 3) ~ 'Physics',
    Q6b.i_y == 1 ~ 'Engineering',
    (Q6b.i_y == 2) | (Q6b.i_y == 3) ~ 'Other science',
    Q6b.i_y == 4 ~ 'Other',
    (Q6b_x == 1) | (Q6b_x == 2) | (Q6b_x == 3) ~ 'Physics',
    Q6b.i_x == 1 ~ 'Engineering',
    (Q6b.i_x == 2) | (Q6b.i_x == 3) ~ 'Other science',
    Q6b.i_x == 4 ~ 'Other',
    TRUE ~ 'Unknown'),
  Gender = case_when(
    (Q6e_3_y == 1) | (Q6e_7_y == 1) ~ 'Non-binary',
    Q6e_2_y == 1 ~ 'Woman',
    Q6e_1_y == 1 ~ 'Man',
    (Q6e_3_x == 1) | (Q6e_7_x == 1) ~ 'Non-binary',
    Q6e_2_x == 1 ~ 'Woman',
    Q6e_1_x == 1 ~ 'Man',
    TRUE ~ 'Unknown'
  ),
  Race.ethnicity.Other = 1 * ((Q6f_1_y == 1) | (Q6f_3_y == 1) | (Q6f_5_y == 1) |
                                (Q6f_7_y == 1) | (Q6f_1_x == 1) | (Q6f_3_x == 1) |
                                (Q6f_5_x == 1) | (Q6f_7_y == 1)),
  Race.ethnicity.Hispanic = 1 * ((Q6f_4_y == 1) | (Q6f_4_x == 1)),
  Race.ethnicity.Asian = 1 * ((Q6f_2_y == 1) | (Q6f_2_x == 1)),
  Race.ethnicity.White = 1 * ((Q6f_6_y == 1) | (Q6f_6_x == 1)),
  Race.ethnicity.Unknown = 1 * ((Race.ethnicity.Other == 0) &
                                  (Race.ethnicity.Hispanic == 0) &
                                  (Race.ethnicity.Asian == 0) &
                                  (Race.ethnicity.White == 0))) %>%
  mutate(Major = relevel(as.factor(Major), ref = 'Physics'),
         Gender = relevel(as.factor(Gender), ref = 'Man'),
         Lab_Purpose = relevel(as.factor(Lab_Purpose), ref = 'Concepts'),
         Lab_Level = relevel(as.factor(Lab_Level), ref = 'FY.Alg'))

df.matched[is.na(df.matched)] <- 0
df.matched[names(df.matched) %like% "Race"] <-
  lapply(df.matched[names(df.matched) %like% "Race"], factor, levels = c(1, 0))
df.matched[names(df.matched) %like% "Race"] <-
  lapply(df.matched[names(df.matched) %like% "Race"], relevel, ref = '0')
```

Demographic breakdowns

```
Race.ethnicity.cols <- names(df.matched)[names(df.matched) %like% 'Race']
Race.ethnicity.table <- function(df, Lab.Purpose = FALSE){
  if(Lab.Purpose){
    for(col in Race.ethnicity.cols){
      print(col)
      print(table(df[, col], df$Lab_Purpose))
    }
```

```r
  } else {
    for(col in Race.ethnicity.cols){
      print(col)
      print(table(df[, col]))
    }
  }
}

table(df.matched$Gender)
```

```
##
##        Man Non-binary    Unknown      Woman
##       2835         56         31       2096
```

```r
Race.ethnicity.table(df.matched)
```

```
## [1] "Race.ethnicity.Other"
##
##    0    1
## 4615  403
## [1] "Race.ethnicity.Hispanic"
##
##    0    1
## 4544  474
## [1] "Race.ethnicity.Asian"
##
##    0    1
## 3485 1533
## [1] "Race.ethnicity.White"
##
##    0    1
## 1994 3024
## [1] "Race.ethnicity.Unknown"
##
##    0    1
## 5018    0
```

```r
table(df.matched$Major)
```

```
##
##       Physics   Engineering         Other Other science       Unknown
##           941          2179           372          1425           101
```

```r
table(df.matched$Lab_Purpose)
```

```
##
## Concepts     Both   Skills
##     2024      800     2194
```

```r
table(df.matched$Gender, df.matched$Lab_Purpose)
```

```
##
##               Concepts Both Skills
##   Man             1174  452   1209
##   Non-binary        11   14     31
##   Unknown           10    5     16
##   Woman            829  329    938
```

```r
Race.ethnicity.table(df.matched, Lab.Purpose = TRUE)
```

```
## [1] "Race.ethnicity.Other"
##
##     Concepts Both Skills
##   0     1909  721   1985
##   1      115   79    209
## [1] "Race.ethnicity.Hispanic"
##
##     Concepts Both Skills
##   0     1872  722   1950
##   1      152   78    244
## [1] "Race.ethnicity.Asian"
##
##     Concepts Both Skills
##   0     1300  641   1544
##   1      724  159    650
## [1] "Race.ethnicity.White"
##
##     Concepts Both Skills
##   0      838  261    895
##   1     1186  539   1299
## [1] "Race.ethnicity.Unknown"
##
##     Concepts Both Skills
##   0     2024  800   2194
##   1        0    0      0
```

```r
table(df.matched$Major, df.matched$Lab_Purpose)
```

```
##
##                  Concepts Both Skills
##   Physics             166  179    596
##   Engineering        1540   74    565
##   Other                48  105    219
##   Other science       230  427    768
##   Unknown              40   15     46
```

```r
chisq.test(df.matched[!duplicated(df.matched$Class_ID), 'Lab_Purpose'],
           df.matched[!duplicated(df.matched$Class_ID), 'Lab_Level'])
```

```
## Warning in chisq.test(df.matched[!duplicated(df.matched$Class_ID),
## "Lab_Purpose"], : Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  df.matched[!duplicated(df.matched$Class_ID), "Lab_Purpose"] and df.matched[!duplicated(df.mat
## X-squared = 13.466, df = 4, p-value = 0.009209
```

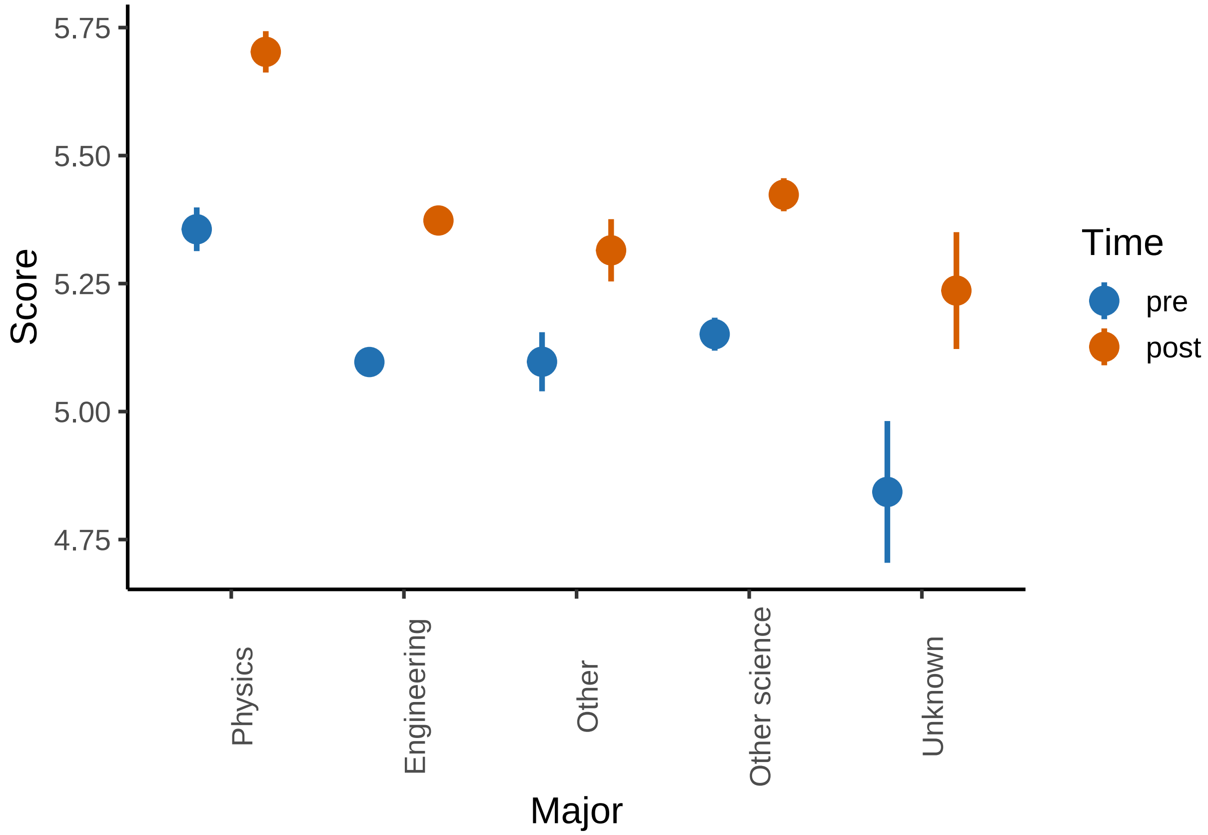
```
summary(aov(PreScores ~ Lab_Purpose, df.matched))
```

```
##               Df Sum Sq Mean Sq F value  Pr(>F)
## Lab_Purpose    2     19   9.284   5.793 0.00307 **
## Residuals   5015   8037   1.603
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Descriptive statistics

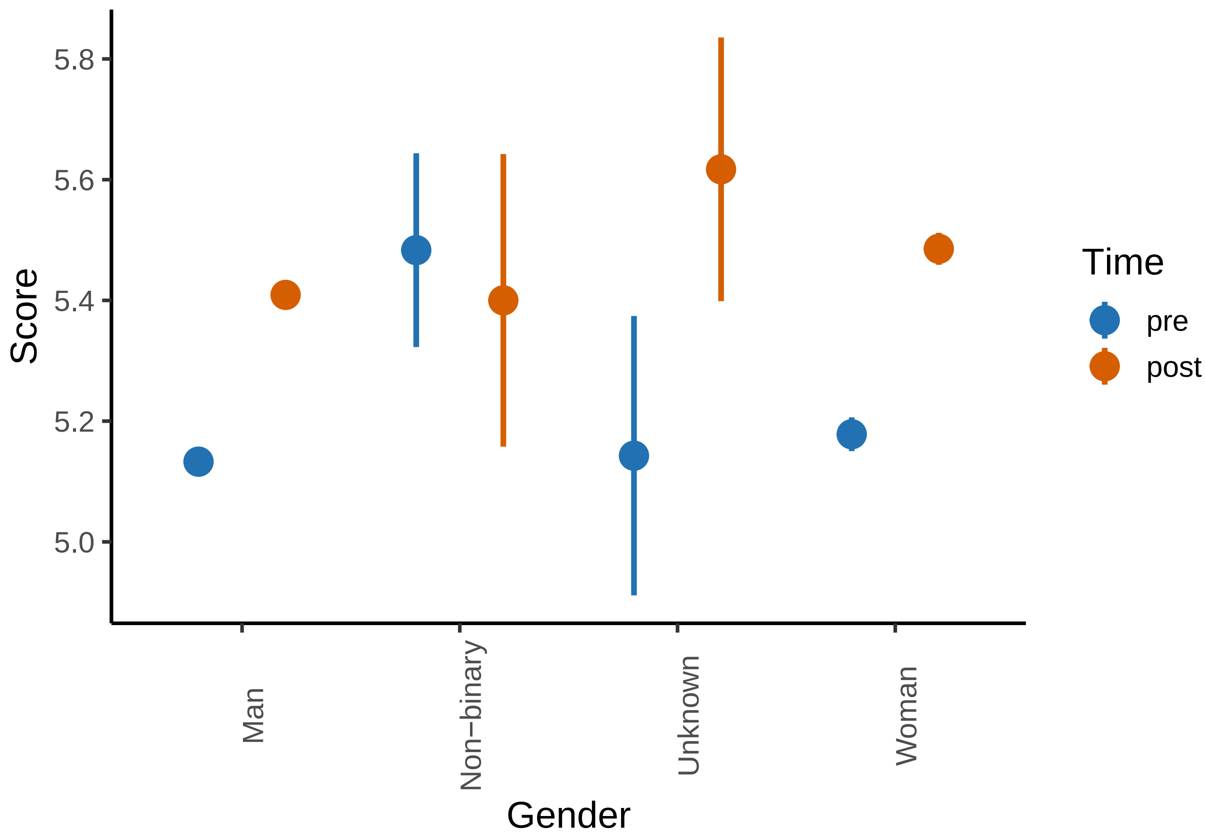
```
plot.pre.post <- function(df, var){
  if(var == 'Race.ethnicity'){
    print(colSums(sapply(df[, names(df) %like% "Race"],
                         function (x) as.numeric(as.character(x)))))

    df.long <- reshape2::melt(df.matched, id.vars = names(df)[names(df) %like% "Race"],
                              measure.vars = c('PreScores', 'PostScores'),
                              variable.name = 'Time', value.name = 'Score') %>%
      reshape2::melt(., measure.vars = names(df)[names(df) %like% "Race"],
                     id.vars = c('Time', 'Score'), variable.name = 'Race.ethnicity') %>%
      filter(value == 1) %>%
      select(Time, Score, Race.ethnicity) %>%
      rowwise() %>%
      mutate(Race.ethnicity = strsplit(as.character(Race.ethnicity), '\\.')[[1]][3])

  } else {
    print(table(df[, var]))
    df.long <- reshape2::melt(df, measure.vars = c('PreScores', 'PostScores'),
                              variable.name = 'Time', value.name = 'Score')
  }

  p <- ggplot(df.long, aes_string(x = var, y = 'Score', group = 'Time', color = 'Time'))
  add_summary(p, fun = 'mean_se', group = c('Time')) +
    scale_color_manual(labels = c('pre', 'post'), values = c('#2271B2', '#D55E00')) +
    theme(axis.text.x = element_text(angle = 90))
}

plot.pre.post(df.matched, 'Major')
```

```
##
##       Physics   Engineering         Other Other science       Unknown
##           941          2179           372          1425           101
```



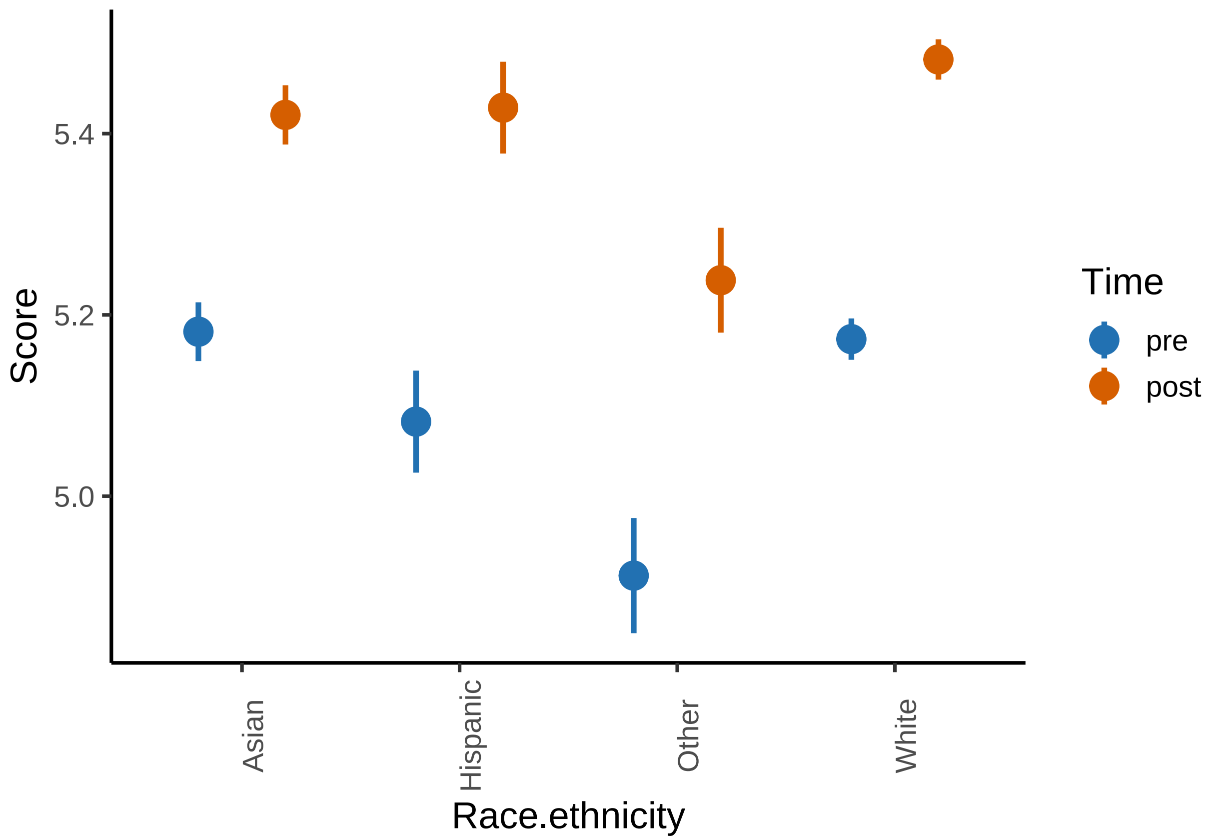

```
plot.pre.post(df.matched, 'Gender')
```

```
##
##        Man Non-binary    Unknown      Woman
##       2835         56         31       2096
```



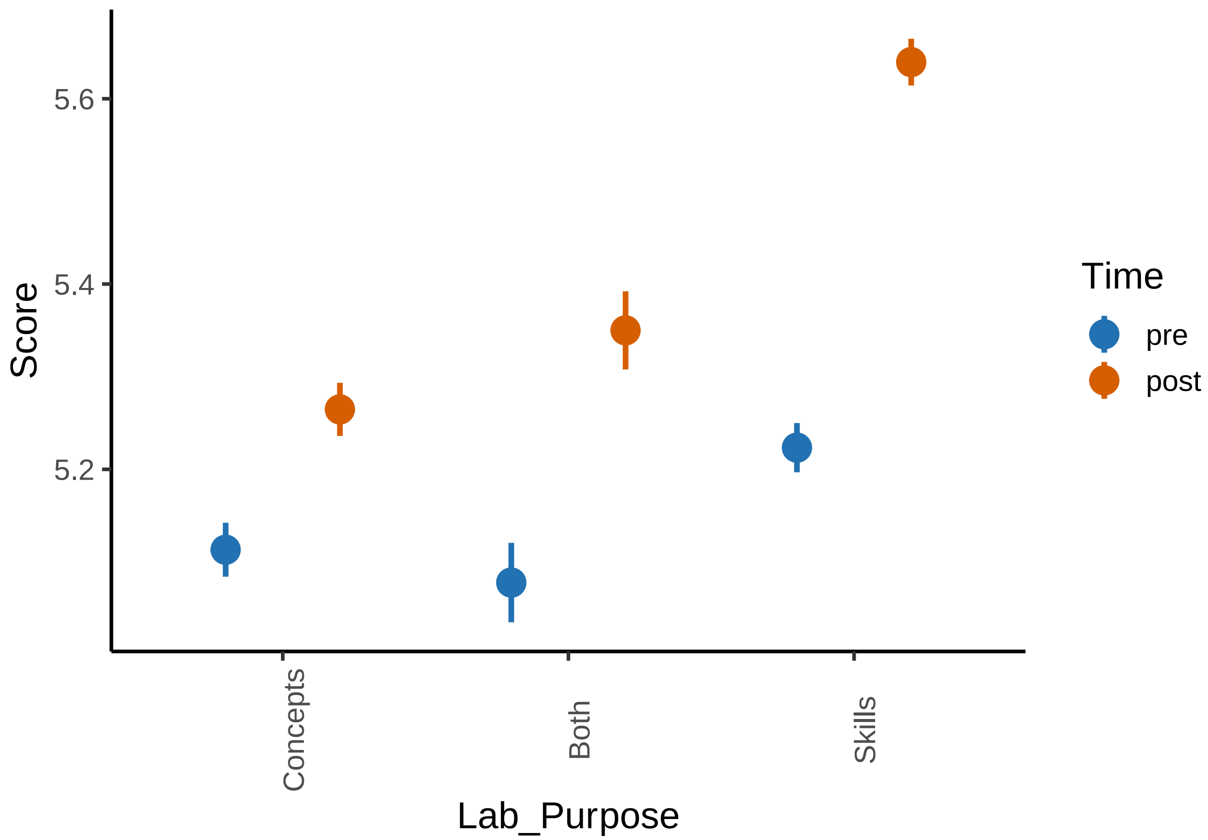

```
plot.pre.post(df.matched, 'Race.ethnicity')
```

```
##     Race.ethnicity.Other Race.ethnicity.Hispanic     Race.ethnicity.Asian
##                      403                     474                     1533
##     Race.ethnicity.White  Race.ethnicity.Unknown
##                     3024                       0
```




```
plot.pre.post(df.matched, 'Lab_Purpose')
```

```
##
## Concepts      Both    Skills
##     2024       800      2194
```



Mixed-effects models

```
mod0 <- lmer(PostScores ~ (1 | Class_ID), df.matched)
r2(mod0)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | Class_ID PostScores ~ 1 NA
##
##    Marginal R2: 0.000
## Conditional R2: 0.117
```

```
mod1 <- lmer(PostScores ~ PreScores + Lab_Purpose + Lab_Level + Major + Gender +
               Race.ethnicity.Other + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
               Race.ethnicity.White + (1 | Class_ID), df.matched)
summary(mod1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
```

```
## PostScores ~ PreScores + Lab_Purpose + Lab_Level + Major + Gender +
##     Race.ethnicity.Other + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##     Race.ethnicity.White + (1 | Class_ID)
##    Data: df.matched
##
## REML criterion at convergence: 15776.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.8662 -0.5774  0.0650  0.6621  3.5079
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Class_ID (Intercept) 0.0855   0.2924
##  Residual             1.3197   1.1488
## Number of obs: 5018, groups:  Class_ID, 87
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              3.726e+00  1.823e-01  1.158e+02  20.437  < 2e-16
## PreScores                2.283e-01  1.338e-02  4.919e+03  17.062  < 2e-16
## Lab_PurposeBoth         -9.454e-02  1.236e-01  6.516e+01  -0.765  0.44693
## Lab_PurposeSkills        2.769e-01  1.064e-01  5.131e+01   2.602  0.01209
## Lab_LevelBFY             7.028e-01  1.615e-01  9.420e+01   4.351 3.43e-05
## Lab_LevelFY.Calc         4.342e-01  1.347e-01  5.785e+01   3.224  0.00208
## MajorEngineering        -1.087e-01  6.230e-02  3.436e+03  -1.745  0.08100
## MajorOther              -9.316e-02  8.078e-02  4.818e+03  -1.153  0.24883
## MajorOther science      -1.809e-03  6.410e-02  4.128e+03  -0.028  0.97748
## MajorUnknown            -1.728e-01  1.274e-01  4.994e+03  -1.356  0.17530
## GenderNon-binary        -1.822e-01  1.568e-01  4.998e+03  -1.162  0.24518
## GenderUnknown            1.424e-01  2.135e-01  4.968e+03   0.667  0.50478
## GenderWoman              5.581e-02  3.509e-02  4.979e+03   1.591  0.11175
## Race.ethnicity.Other1   -1.869e-01  6.599e-02  4.981e+03  -2.832  0.00464
## Race.ethnicity.Hispanic1 -2.289e-02  6.163e-02  5.000e+03  -0.371  0.71037
## Race.ethnicity.Asian1   -6.283e-02  5.615e-02  4.996e+03  -1.119  0.26321
## Race.ethnicity.White1    1.322e-01  5.313e-02  4.997e+03   2.487  0.01290
##
## (Intercept)             ***
## PreScores               ***
## Lab_PurposeBoth
## Lab_PurposeSkills       *
## Lab_LevelBFY            ***
## Lab_LevelFY.Calc        **
## MajorEngineering        .
## MajorOther
## MajorOther science
## MajorUnknown
## GenderNon-binary
## GenderUnknown
## GenderWoman
## Race.ethnicity.Other1   **
## Race.ethnicity.Hispanic1
## Race.ethnicity.Asian1
## Race.ethnicity.White1   *
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 17 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
mod2 <- lmer(PostScores ~ PreScores + Lab_Level + Major + Lab_Purpose * (Gender +
               Race.ethnicity.Other + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
               Race.ethnicity.White) + (1 | Class_ID), df.matched)
summary(mod2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## PostScores ~ PreScores + Lab_Level + Major + Lab_Purpose * (Gender +
##     Race.ethnicity.Other + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##     Race.ethnicity.White) + (1 | Class_ID)
##    Data: df.matched
##
## REML criterion at convergence: 15791.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.7871 -0.5731  0.0636  0.6559  3.4679
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Class_ID (Intercept) 0.08488  0.2913
##  Residual             1.32135  1.1495
## Number of obs: 5018, groups:  Class_ID, 87
##
## Fixed effects:
##                                             Estimate Std. Error
## (Intercept)                                3.737e+00  1.941e-01
## PreScores                                  2.279e-01  1.340e-02
## Lab_LevelBFY                               6.959e-01  1.614e-01
## Lab_LevelFY.Calc                           4.328e-01  1.347e-01
## MajorEngineering                          -1.031e-01  6.239e-02
## MajorOther                                -9.793e-02  8.095e-02
## MajorOther science                        -6.883e-04  6.424e-02
## MajorUnknown                              -1.702e-01  1.278e-01
## Lab_PurposeBoth                           -2.739e-01  2.010e-01
## Lab_PurposeSkills                          3.156e-01  1.570e-01
## GenderNon-binary                           2.180e-01  3.520e-01
## GenderUnknown                              1.508e-01  3.736e-01
## GenderWoman                                8.451e-02  5.440e-02
## Race.ethnicity.Other1                     -1.429e-01  1.181e-01
## Race.ethnicity.Hispanic1                  -2.948e-02  1.047e-01
## Race.ethnicity.Asian1                     -5.920e-02  8.986e-02
## Race.ethnicity.White1                      8.428e-02  8.693e-02
## Lab_PurposeBoth:GenderNon-binary          -3.963e-01  4.749e-01
```

```
## Lab_PurposeSkills:GenderNon-binary         -5.638e-01  4.101e-01
## Lab_PurposeBoth:GenderUnknown              -2.912e-01  6.451e-01
## Lab_PurposeSkills:GenderUnknown             5.232e-02  4.766e-01
## Lab_PurposeBoth:GenderWoman                 6.165e-02  1.058e-01
## Lab_PurposeSkills:GenderWoman              -8.629e-02  7.602e-02
## Lab_PurposeBoth:Race.ethnicity.Other1       7.096e-02  1.963e-01
## Lab_PurposeSkills:Race.ethnicity.Other1    -1.007e-01  1.502e-01
## Lab_PurposeBoth:Race.ethnicity.Hispanic1    8.272e-02  1.973e-01
## Lab_PurposeSkills:Race.ethnicity.Hispanic1 -8.376e-03  1.357e-01
## Lab_PurposeBoth:Race.ethnicity.Asian1       4.582e-02  1.732e-01
## Lab_PurposeSkills:Race.ethnicity.Asian1    -3.885e-02  1.223e-01
## Lab_PurposeBoth:Race.ethnicity.White1       2.042e-01  1.624e-01
## Lab_PurposeSkills:Race.ethnicity.White1     3.707e-02  1.164e-01
##                                                    df t value Pr(>|t|)
## (Intercept)                                 1.491e+02  19.250  < 2e-16 ***
## PreScores                                   4.908e+03  17.007  < 2e-16 ***
## Lab_LevelBFY                                9.289e+01   4.310 4.05e-05 ***
## Lab_LevelFY.Calc                            5.732e+01   3.213  0.00216 **
## MajorEngineering                            3.410e+03  -1.652  0.09854 .
## MajorOther                                  4.794e+03  -1.210  0.22647
## MajorOther science                          4.107e+03  -0.011  0.99145
## MajorUnknown                                4.981e+03  -1.331  0.18319
## Lab_PurposeBoth                             4.228e+02  -1.363  0.17360
## Lab_PurposeSkills                           2.391e+02   2.010  0.04556 *
## GenderNon-binary                            4.939e+03   0.619  0.53580
## GenderUnknown                               4.935e+03   0.404  0.68645
## GenderWoman                                 4.983e+03   1.554  0.12036
## Race.ethnicity.Other1                       4.934e+03  -1.210  0.22624
## Race.ethnicity.Hispanic1                    4.946e+03  -0.282  0.77821
## Race.ethnicity.Asian1                       4.949e+03  -0.659  0.51005
## Race.ethnicity.White1                       4.949e+03   0.970  0.33233
## Lab_PurposeBoth:GenderNon-binary            4.986e+03  -0.835  0.40399
## Lab_PurposeSkills:GenderNon-binary          4.947e+03  -1.375  0.16925
## Lab_PurposeBoth:GenderUnknown               4.971e+03  -0.451  0.65168
## Lab_PurposeSkills:GenderUnknown             4.944e+03   0.110  0.91259
## Lab_PurposeBoth:GenderWoman                 4.607e+03   0.583  0.56007
## Lab_PurposeSkills:GenderWoman               4.981e+03  -1.135  0.25643
## Lab_PurposeBoth:Race.ethnicity.Other1       4.975e+03   0.361  0.71783
## Lab_PurposeSkills:Race.ethnicity.Other1     4.948e+03  -0.670  0.50258
## Lab_PurposeBoth:Race.ethnicity.Hispanic1    4.895e+03   0.419  0.67498
## Lab_PurposeSkills:Race.ethnicity.Hispanic1  4.962e+03  -0.062  0.95078
## Lab_PurposeBoth:Race.ethnicity.Asian1       4.980e+03   0.264  0.79143
## Lab_PurposeSkills:Race.ethnicity.Asian1     4.973e+03  -0.318  0.75082
## Lab_PurposeBoth:Race.ethnicity.White1       4.970e+03   1.257  0.20875
## Lab_PurposeSkills:Race.ethnicity.White1     4.965e+03   0.318  0.75012
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 31 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
r2(mod1)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | Class_ID PostScores ~ PreScores + Lab_Purpose + Lab_Level + Major + Gender + Race.ethni
##
##    Marginal R2: 0.101
## Conditional R2: 0.156
```

```r
r2(mod2)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | Class_ID PostScores ~ PreScores + Lab_Level + Major + Lab_Purpose * (Gender + Race.ethn
##
##    Marginal R2: 0.102
## Conditional R2: 0.157
```

```r
noStandard.cols <- c('Lab_Purpose', 'Lab_Level', 'Major', 'Gender',
                     names(df.matched)[names(df.matched) %like% "Race"])
class(mod1) <- "lmerMod"
class(mod2) <- "lmerMod"
beta(mod1, skip = noStandard.cols)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: PostScores.z ~ PreScores.z + Lab_Purpose + Lab_Level + Major +
##     Gender + Race.ethnicity.Other + Race.ethnicity.Hispanic +
##     Race.ethnicity.Asian + Race.ethnicity.White + (1 | Class_ID)
##    Data: data
##
## REML criterion at convergence: 13626.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.8662 -0.5774  0.0650  0.6621  3.5079
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Class_ID (Intercept) 0.05563  0.2359
##  Residual             0.85866  0.9266
## Number of obs: 5018, groups:  Class_ID, 87
##
## Fixed effects:
##                          Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              -0.43524    0.13630   86.52209  -3.193  0.00196
## PreScores.z               0.23334    0.01368 4919.36997  17.062  < 2e-16
## Lab_PurposeBoth          -0.07626    0.09966   65.16429  -0.765  0.44693
```

```
## Lab_PurposeSkills           0.22333    0.08583   51.31038   2.602  0.01209
## Lab_LevelBFY                0.56689    0.13028   94.20112   4.351 3.43e-05
## Lab_LevelFY.Calc            0.35028    0.10866   57.85365   3.224  0.00208
## MajorEngineering           -0.08771    0.05025 3435.93912  -1.745  0.08100
## MajorOther                 -0.07515    0.06516 4817.79239  -1.153  0.24883
## MajorOther science         -0.00146    0.05171 4127.89954  -0.028  0.97748
## MajorUnknown               -0.13936    0.10280 4994.23373  -1.356  0.17530
## GenderNon-binary           -0.14696    0.12645 4998.38031  -1.162  0.24518
## GenderUnknown               0.11490    0.17226 4967.70599   0.667  0.50478
## GenderWoman                 0.04502    0.02830 4979.30630   1.591  0.11175
## Race.ethnicity.Other1      -0.15076    0.05323 4981.49964  -2.832  0.00464
## Race.ethnicity.Hispanic1   -0.01846    0.04971 4999.50753  -0.371  0.71037
## Race.ethnicity.Asian1      -0.05068    0.04529 4995.67693  -1.119  0.26321
## Race.ethnicity.White1       0.10660    0.04286 4997.07351   2.487  0.01290
##
## (Intercept)              **
## PreScores.z              ***
## Lab_PurposeBoth
## Lab_PurposeSkills        *
## Lab_LevelBFY             ***
## Lab_LevelFY.Calc         **
## MajorEngineering         .
## MajorOther
## MajorOther science
## MajorUnknown
## GenderNon-binary
## GenderUnknown
## GenderWoman
## Race.ethnicity.Other1    **
## Race.ethnicity.Hispanic1
## Race.ethnicity.Asian1
## Race.ethnicity.White1    *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 17 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
beta(mod2, skip = noStandard.cols)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: PostScores.z ~ PreScores.z + Lab_Level + Major + Lab_Purpose *
##     (Gender + Race.ethnicity.Other + Race.ethnicity.Hispanic +
##         Race.ethnicity.Asian + Race.ethnicity.White) + (1 | Class_ID)
##    Data: data
##
## REML criterion at convergence: 13648.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -4.7871 -0.5731  0.0636  0.6559  3.4679
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Class_ID (Intercept) 0.05523  0.2350
##  Residual             0.85976  0.9272
## Number of obs: 5018, groups:  Class_ID, 87
##
## Fixed effects:
##                                              Estimate Std. Error
## (Intercept)                                -4.275e-01  1.464e-01
## PreScores.z                                 2.329e-01  1.370e-02
## Lab_LevelBFY                                5.613e-01  1.302e-01
## Lab_LevelFY.Calc                            3.491e-01  1.086e-01
## MajorEngineering                           -8.316e-02  5.032e-02
## MajorOther                                 -7.899e-02  6.530e-02
## MajorOther science                         -5.552e-04  5.182e-02
## MajorUnknown                               -1.373e-01  1.031e-01
## Lab_PurposeBoth                            -2.209e-01  1.621e-01
## Lab_PurposeSkills                           2.545e-01  1.266e-01
## GenderNon-binary                            1.758e-01  2.840e-01
## GenderUnknown                               1.217e-01  3.013e-01
## GenderWoman                                 6.817e-02  4.388e-02
## Race.ethnicity.Other1                      -1.153e-01  9.523e-02
## Race.ethnicity.Hispanic1                   -2.378e-02  8.443e-02
## Race.ethnicity.Asian1                      -4.776e-02  7.249e-02
## Race.ethnicity.White1                       6.798e-02  7.012e-02
## Lab_PurposeBoth:GenderNon-binary           -3.197e-01  3.831e-01
## Lab_PurposeSkills:GenderNon-binary         -4.548e-01  3.308e-01
## Lab_PurposeBoth:GenderUnknown              -2.349e-01  5.203e-01
## Lab_PurposeSkills:GenderUnknown             4.220e-02  3.844e-01
## Lab_PurposeBoth:GenderWoman                 4.973e-02  8.533e-02
## Lab_PurposeSkills:GenderWoman              -6.960e-02  6.132e-02
## Lab_PurposeBoth:Race.ethnicity.Other1       5.724e-02  1.584e-01
## Lab_PurposeSkills:Race.ethnicity.Other1    -8.125e-02  1.212e-01
## Lab_PurposeBoth:Race.ethnicity.Hispanic1    6.672e-02  1.591e-01
## Lab_PurposeSkills:Race.ethnicity.Hispanic1 -6.756e-03  1.094e-01
## Lab_PurposeBoth:Race.ethnicity.Asian1       3.696e-02  1.397e-01
## Lab_PurposeSkills:Race.ethnicity.Asian1    -3.133e-02  9.867e-02
## Lab_PurposeBoth:Race.ethnicity.White1       1.647e-01  1.310e-01
## Lab_PurposeSkills:Race.ethnicity.White1     2.990e-02  9.389e-02
##                                                    df t value Pr(>|t|)
## (Intercept)                                 1.151e+02  -2.920  0.00421 **
## PreScores.z                                 4.908e+03  17.007  < 2e-16 ***
## Lab_LevelBFY                                9.289e+01   4.310 4.05e-05 ***
## Lab_LevelFY.Calc                            5.732e+01   3.213  0.00216 **
## MajorEngineering                            3.410e+03  -1.652  0.09854 .
## MajorOther                                  4.794e+03  -1.210  0.22647
## MajorOther science                          4.107e+03  -0.011  0.99145
## MajorUnknown                                4.981e+03  -1.331  0.18319
## Lab_PurposeBoth                             4.228e+02  -1.363  0.17360
## Lab_PurposeSkills                           2.391e+02   2.010  0.04556 *
## GenderNon-binary                            4.939e+03   0.619  0.53580
## GenderUnknown                               4.935e+03   0.404  0.68645
```

```
## GenderWoman                                 4.983e+03   1.554  0.12036
## Race.ethnicity.Other1                       4.934e+03  -1.210  0.22624
## Race.ethnicity.Hispanic1                    4.946e+03  -0.282  0.77821
## Race.ethnicity.Asian1                       4.949e+03  -0.659  0.51005
## Race.ethnicity.White1                       4.949e+03   0.970  0.33233
## Lab_PurposeBoth:GenderNon-binary            4.986e+03  -0.835  0.40399
## Lab_PurposeSkills:GenderNon-binary          4.947e+03  -1.375  0.16925
## Lab_PurposeBoth:GenderUnknown               4.971e+03  -0.451  0.65168
## Lab_PurposeSkills:GenderUnknown             4.944e+03   0.110  0.91259
## Lab_PurposeBoth:GenderWoman                 4.607e+03   0.583  0.56007
## Lab_PurposeSkills:GenderWoman               4.981e+03  -1.135  0.25643
## Lab_PurposeBoth:Race.ethnicity.Other1       4.975e+03   0.361  0.71783
## Lab_PurposeSkills:Race.ethnicity.Other1     4.948e+03  -0.670  0.50258
## Lab_PurposeBoth:Race.ethnicity.Hispanic1    4.895e+03   0.419  0.67498
## Lab_PurposeSkills:Race.ethnicity.Hispanic1  4.962e+03  -0.062  0.95078
## Lab_PurposeBoth:Race.ethnicity.Asian1       4.980e+03   0.264  0.79143
## Lab_PurposeSkills:Race.ethnicity.Asian1     4.973e+03  -0.318  0.75082
## Lab_PurposeBoth:Race.ethnicity.White1       4.970e+03   1.257  0.20875
## Lab_PurposeSkills:Race.ethnicity.White1     4.965e+03   0.318  0.75012
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

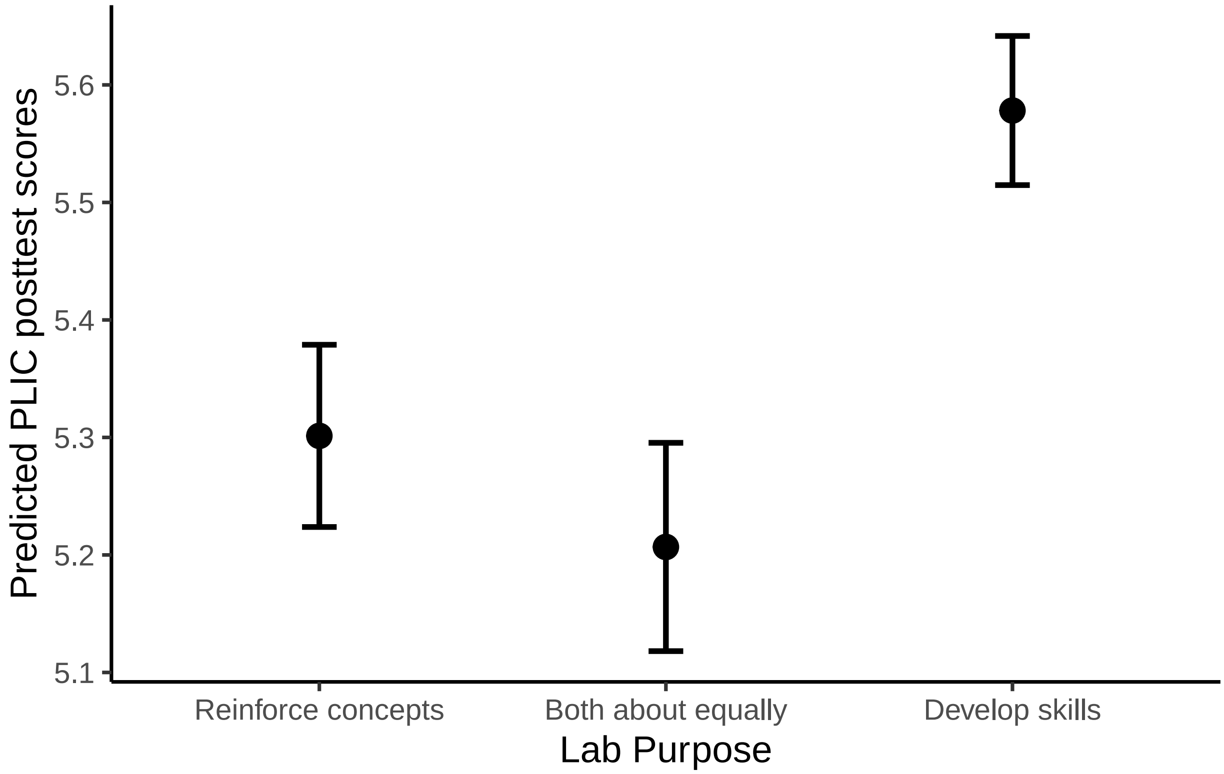
```
##
## Correlation matrix not shown by default, as p = 31 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

Marginal effects plots

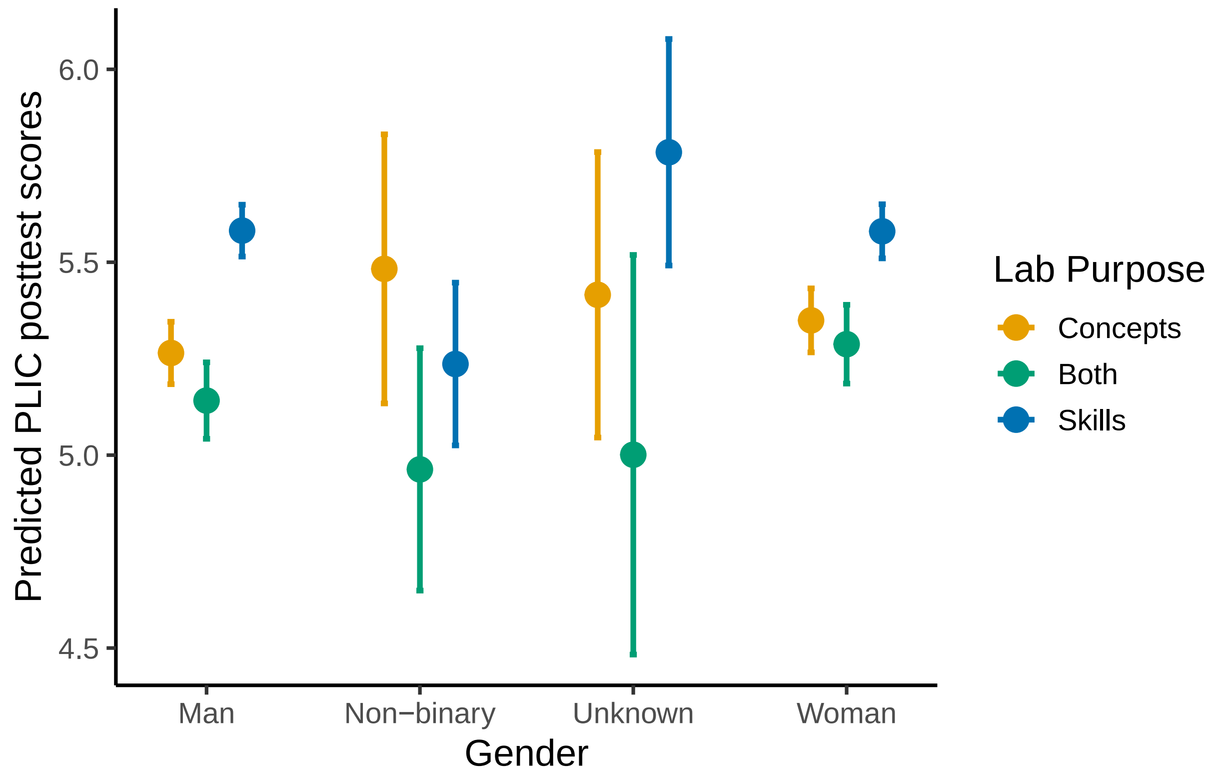
```
# Main effect of lab goal from Model 1
p1 <- plot_model(mod1, type = 'eff', terms = 'Lab_Purpose', dot.size = 4, line.size = 1,
                 ci.lvl = 0.67, title = '',
                 axis.title = 'Predicted PLIC posttest scores',
                 colors = c('#e69f00', '#009e74', '#0071b2'), dodge = 0.5) +
  theme(legend.position = 'right') +
  scale_x_discrete(limits = c("Reinforce concepts", "Both about equally",
                              "Develop skills"))
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which
## will replace the existing scale.
```

```
p1.new <- p1
p1.new$data$x <- c(1, 2, 3)
p1.new
```



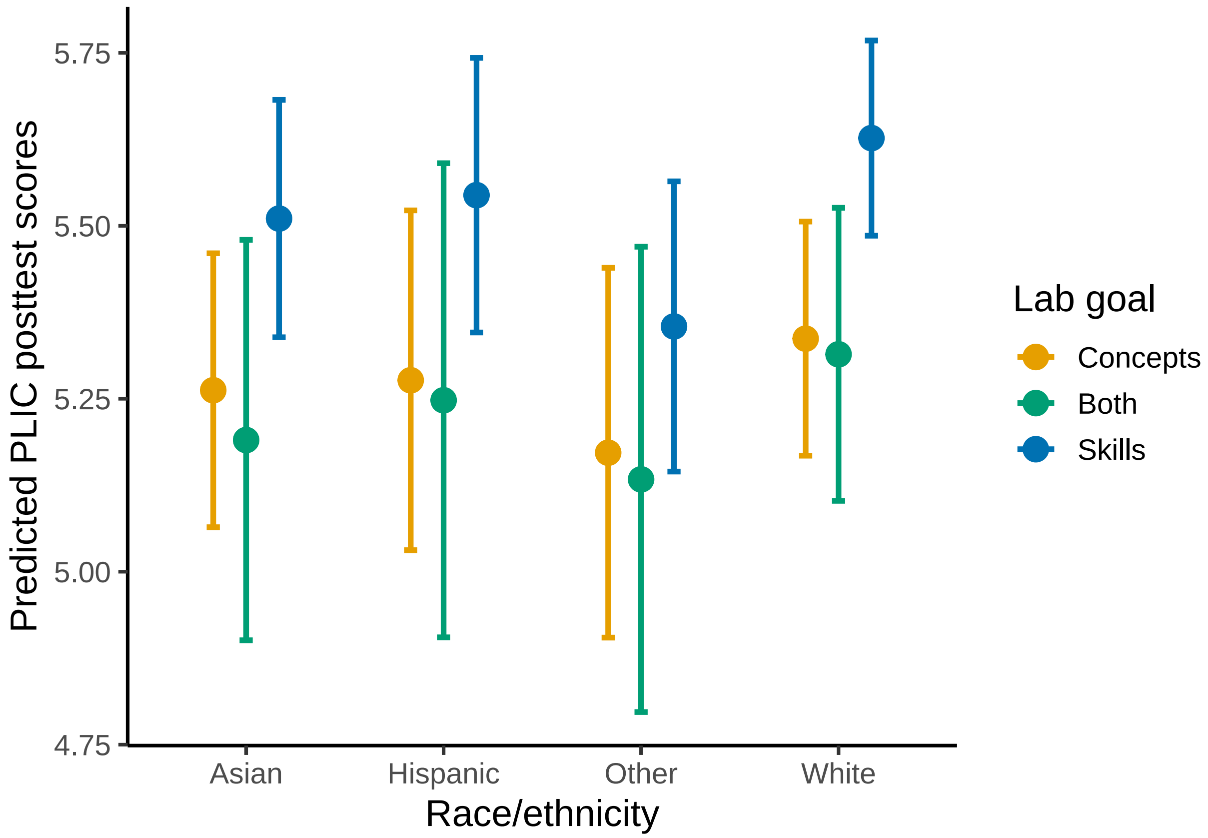

```r
# Effects of gender across lab goal from Model 2

p2 <- plot_model(mod2, type = 'eff', terms = c('Gender', 'Lab_Purpose'), dot.size = 4,
                 line.size = 1, ci.lvl = 0.67, title = '',
                 axis.title = 'Predicted PLIC posttest scores',
                 colors = c('#e69f00', '#009e74', '#0071b2'), dodge = 0.5) +
  theme(legend.position = 'right')

p2.new <- p2
p2.new$data$group <- factor(p2.new$data$group, levels = c("Concepts", "Both", "Skills"))
p2.new
```



Race/ethnicity marginal effects plots

```
p3.other <- plot_model(mod2, type = 'eff', terms = c('Race.ethnicity.Other [1]',
                                                     'Lab_Purpose'))
df.race.eff <- data.frame(p3.other$data) %>%
  mutate(race.ethnicity = 'Race.ethnicity.Other')
for(race in c('Race.ethnicity.Hispanic', 'Race.ethnicity.Asian', 'Race.ethnicity.White')){
  p3 <- plot_model(mod2, type = 'eff', terms = c(paste(race, ' [1]', sep = ''),
                                                 'Lab_Purpose'))
  df.race.eff <- rbind(df.race.eff, data.frame(p3$data) %>%
                         mutate(race.ethnicity = race))
}

df.race.eff <- df.race.eff %>%
  mutate(group = factor(group, levels = c('Concepts', 'Both', 'Skills'),
                        ordered = TRUE)) %>%
  rowwise() %>%
  mutate(race.ethnicity = strsplit(race.ethnicity, '\\.')[[1]][3])

ggplot(df.race.eff, aes(x = race.ethnicity, y = predicted, group = group, color = group)) +
  geom_point(size = 4, position = position_dodge(width = 0.5)) +
  geom_errorbar(aes(ymin = conf.low, ymax = conf.high), size = 1, width = 0.2,
                position = position_dodge(width = 0.5)) +
```

```r
  scale_color_manual(values = c('#e69f00', '#009e74', '#0071b2')) +
  labs(x = 'Race/ethnicity', y = 'Predicted PLIC posttest scores', color = 'Lab goal')
```



Build measurement model for latent class variables

```r
df.matched[, names(df.matched) %like% "Q29|Q31"] <-
  data.frame(lapply(df.matched[, names(df.matched) %like% "Q29|Q31"], function(x)
    droplevels(factor(as.vector(x), levels = c('1', '2', '3', '4', '5'), ordered = TRUE))))

mod <- '
  agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q29_5 + Q31_6
  modeling =~ Q31_1 + Q31_2 + Q31_3 + Q31_4 + Q31_5
'

fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q29|Q31"]))
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 27 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         53
##
```

```
##   Number of observations                            60
##
##   Estimator                                       DWLS      Robust
##   Model Fit Test Statistic                      68.185      82.090
##   Degrees of freedom                                43          43
##   P-value (Chi-square)                           0.009       0.000
##   Scaling correction factor                                  1.076
##   Shift parameter                                           18.702
##     for simple second-order correction (Mplus variant)
##
## Model test baseline model:
##
##   Minimum Function Test Statistic             2408.967    1165.661
##   Degrees of freedom                                55          55
##   P-value                                        0.000       0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.989       0.965
##   Tucker-Lewis Index (TLI)                       0.986       0.955
##
##   Robust Comparative Fit Index (CFI)                            NA
##   Robust Tucker-Lewis Index (TLI)                               NA
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.100       0.124
##   90 Percent Confidence Interval          0.051  0.143       0.083  0.165
##   P-value RMSEA <= 0.05                          0.048       0.004
##
##   Robust RMSEA                                                  NA
##   90 Percent Confidence Interval                                NA     NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.097       0.097
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model        Unstructured
##   Standard Errors                           Robust.sem
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q29_1             1.000                               0.792    0.792
##     Q29_2             1.055    0.097   10.879    0.000    0.835    0.835
##     Q29_3             0.890    0.088   10.084    0.000    0.705    0.705
##     Q29_4             1.134    0.087   12.990    0.000    0.898    0.898
##     Q29_5             0.811    0.102    7.945    0.000    0.643    0.643
##     Q31_6             0.921    0.096    9.586    0.000    0.730    0.730
##   modeling =~
##     Q31_1             1.000                               0.901    0.901
```

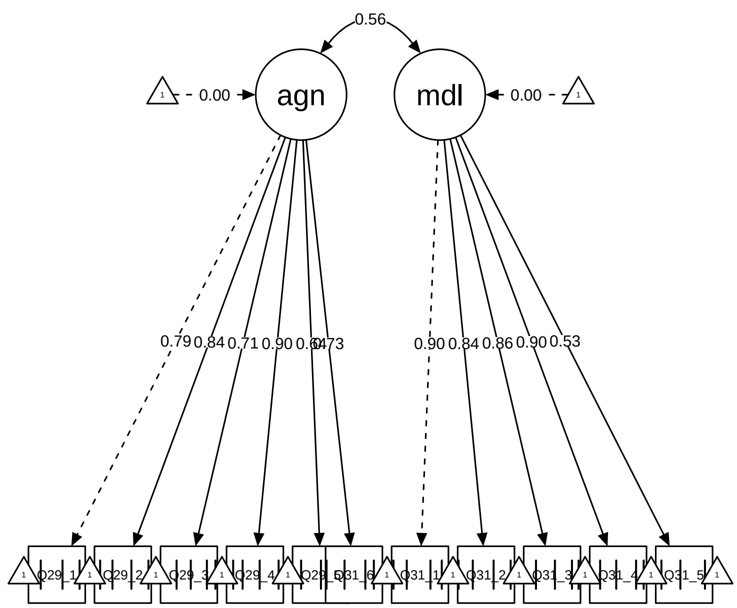
```
##     Q31_2             0.931    0.080   11.706    0.000    0.839    0.839
##     Q31_3             0.958    0.061   15.678    0.000    0.863    0.863
##     Q31_4             0.996    0.059   16.940    0.000    0.897    0.897
##     Q31_5             0.583    0.109    5.344    0.000    0.526    0.526
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~~
##     modeling          0.399    0.069    5.789    0.000    0.559    0.559
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.000                               0.000    0.000
##    .Q29_2             0.000                               0.000    0.000
##    .Q29_3             0.000                               0.000    0.000
##    .Q29_4             0.000                               0.000    0.000
##    .Q29_5             0.000                               0.000    0.000
##    .Q31_6             0.000                               0.000    0.000
##    .Q31_1             0.000                               0.000    0.000
##    .Q31_2             0.000                               0.000    0.000
##    .Q31_3             0.000                               0.000    0.000
##    .Q31_4             0.000                               0.000    0.000
##    .Q31_5             0.000                               0.000    0.000
##     agency            0.000                               0.000    0.000
##     modeling          0.000                               0.000    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     Q29_1|t1         -0.784    0.183   -4.288    0.000   -0.784   -0.784
##     Q29_1|t2          0.253    0.165    1.535    0.125    0.253    0.253
##     Q29_1|t3          1.282    0.223    5.759    0.000    1.282    1.282
##     Q29_2|t1         -1.282    0.223   -5.759    0.000   -1.282   -1.282
##     Q29_2|t2         -0.477    0.170   -2.805    0.005   -0.477   -0.477
##     Q29_2|t3          0.385    0.168    2.298    0.022    0.385    0.385
##     Q29_2|t4          1.645    0.275    5.979    0.000    1.645    1.645
##     Q29_3|t1         -0.573    0.173   -3.307    0.001   -0.573   -0.573
##     Q29_3|t2          0.084    0.163    0.512    0.609    0.084    0.084
##     Q29_3|t3          0.903    0.190    4.757    0.000    0.903    0.903
##     Q29_3|t4          1.834    0.315    5.825    0.000    1.834    1.834
##     Q29_4|t1         -1.192    0.213   -5.592    0.000   -1.192   -1.192
##     Q29_4|t2         -0.573    0.173   -3.307    0.001   -0.573   -0.573
##     Q29_4|t3          0.210    0.164    1.279    0.201    0.210    0.210
##     Q29_4|t4          1.383    0.235    5.893    0.000    1.383    1.383
##     Q29_5|t1         -1.036    0.199   -5.198    0.000   -1.036   -1.036
##     Q29_5|t2          0.000    0.163    0.000    1.000    0.000    0.000
##     Q29_5|t3          0.728    0.180    4.046    0.000    0.728    0.728
##     Q31_6|t1         -2.128    0.402   -5.293    0.000   -2.128   -2.128
##     Q31_6|t2         -0.431    0.169   -2.552    0.011   -0.431   -0.431
##     Q31_6|t3          0.524    0.172    3.056    0.002    0.524    0.524
##     Q31_6|t4          1.036    0.199    5.198    0.000    1.036    1.036
##     Q31_1|t1         -1.834    0.315   -5.825    0.000   -1.834   -1.834
##     Q31_1|t2         -0.623    0.175   -3.555    0.000   -0.623   -0.623
##     Q31_1|t3          0.477    0.170    2.805    0.005    0.477    0.477
##     Q31_1|t4          1.192    0.213    5.592    0.000    1.192    1.192
```

```
##     Q31_2|t1         -2.128    0.402   -5.293    0.000   -2.128   -2.128
##     Q31_2|t2         -0.623    0.175   -3.555    0.000   -0.623   -0.623
##     Q31_2|t3          0.341    0.167    2.044    0.041    0.341    0.341
##     Q31_2|t4          1.501    0.251    5.977    0.000    1.501    1.501
##     Q31_3|t1         -0.784    0.183   -4.288    0.000   -0.784   -0.784
##     Q31_3|t2          0.126    0.164    0.768    0.443    0.126    0.126
##     Q31_3|t3          1.036    0.199    5.198    0.000    1.036    1.036
##     Q31_3|t4          1.834    0.315    5.825    0.000    1.834    1.834
##     Q31_4|t1         -0.903    0.190   -4.757    0.000   -0.903   -0.903
##     Q31_4|t2         -0.084    0.163   -0.512    0.609   -0.084   -0.084
##     Q31_4|t3          0.903    0.190    4.757    0.000    0.903    0.903
##     Q31_4|t4          1.645    0.275    5.979    0.000    1.645    1.645
##     Q31_5|t1         -1.282    0.223   -5.759    0.000   -1.282   -1.282
##     Q31_5|t2         -0.168    0.164   -1.024    0.306   -0.168   -0.168
##     Q31_5|t3          1.111    0.206    5.403    0.000    1.111    1.111
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.373                                0.373    0.373
##    .Q29_2             0.302                                0.302    0.302
##    .Q29_3             0.503                                0.503    0.503
##    .Q29_4             0.193                                0.193    0.193
##    .Q29_5             0.587                                0.587    0.587
##    .Q31_6             0.468                                0.468    0.468
##    .Q31_1             0.188                                0.188    0.188
##    .Q31_2             0.296                                0.296    0.296
##    .Q31_3             0.255                                0.255    0.255
##    .Q31_4             0.195                                0.195    0.195
##    .Q31_5             0.724                                0.724    0.724
##     agency            0.627    0.092    6.785    0.000    1.000    1.000
##     modeling          0.812    0.084    9.629    0.000    1.000    1.000
##
## Scales y*:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##     Q29_1             1.000                                1.000    1.000
##     Q29_2             1.000                                1.000    1.000
##     Q29_3             1.000                                1.000    1.000
##     Q29_4             1.000                                1.000    1.000
##     Q29_5             1.000                                1.000    1.000
##     Q31_6             1.000                                1.000    1.000
##     Q31_1             1.000                                1.000    1.000
##     Q31_2             1.000                                1.000    1.000
##     Q31_3             1.000                                1.000    1.000
##     Q31_4             1.000                                1.000    1.000
##     Q31_5             1.000                                1.000    1.000
##
## Modification Indices:
##
##          lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 91    agency =~ Q31_1  0.785  0.109   0.086    0.086    0.086
## 92    agency =~ Q31_2 14.051 -0.452  -0.358   -0.358   -0.358
## 93    agency =~ Q31_3  6.602  0.342   0.271    0.271    0.271
## 94    agency =~ Q31_4  0.521  0.099   0.078    0.078    0.078
## 95    agency =~ Q31_5  0.241 -0.071  -0.056   -0.056   -0.056
```

```
## 96  modeling =~ Q29_1  4.552  0.257   0.231    0.231    0.231
## 97  modeling =~ Q29_2  4.599 -0.240  -0.216   -0.216   -0.216
## 98  modeling =~ Q29_3  0.329 -0.061  -0.055   -0.055   -0.055
## 99  modeling =~ Q29_4  0.318  0.065   0.058    0.058    0.058
## 100 modeling =~ Q29_5  0.512  0.080   0.072    0.072    0.072
## 101 modeling =~ Q31_6  0.157 -0.042  -0.037   -0.037   -0.037
## 102    Q29_1 ~~ Q29_2  0.130 -0.033  -0.033   -0.099   -0.099
## 103    Q29_1 ~~ Q29_3  0.542 -0.084  -0.084   -0.195   -0.195
## 104    Q29_1 ~~ Q29_4  0.416 -0.066  -0.066   -0.246   -0.246
## 105    Q29_1 ~~ Q29_5  1.791 -0.160  -0.160   -0.342   -0.342
## 106    Q29_1 ~~ Q31_6  0.428  0.067   0.067    0.161    0.161
## 107    Q29_1 ~~ Q31_1  0.907  0.101   0.101    0.383    0.383
## 108    Q29_1 ~~ Q31_2  0.608  0.094   0.094    0.282    0.282
## 109    Q29_1 ~~ Q31_3  0.936  0.124   0.124    0.403    0.403
## 110    Q29_1 ~~ Q31_4  1.484  0.152   0.152    0.563    0.563
## 111    Q29_1 ~~ Q31_5  0.002 -0.007  -0.007   -0.013   -0.013
## 112    Q29_2 ~~ Q29_3  4.185  0.177   0.177    0.454    0.454
## 113    Q29_2 ~~ Q29_4  1.863  0.123   0.123    0.510    0.510
## 114    Q29_2 ~~ Q29_5  0.035 -0.021  -0.021   -0.050   -0.050
## 115    Q29_2 ~~ Q31_6  1.759 -0.146  -0.146   -0.389   -0.389
## 116    Q29_2 ~~ Q31_1  0.002  0.004   0.004    0.017    0.017
## 117    Q29_2 ~~ Q31_2  5.115 -0.233  -0.233   -0.778   -0.778
## 118    Q29_2 ~~ Q31_3  0.041 -0.023  -0.023   -0.082   -0.082
## 119    Q29_2 ~~ Q31_4  1.306 -0.139  -0.139   -0.571   -0.571
## 120    Q29_2 ~~ Q31_5  0.546 -0.097  -0.097   -0.207   -0.207
## 121    Q29_3 ~~ Q29_4  2.920 -0.216  -0.216   -0.692   -0.692
## 122    Q29_3 ~~ Q29_5  2.098  0.174   0.174    0.321    0.321
## 123    Q29_3 ~~ Q31_6  0.846 -0.114  -0.114   -0.236   -0.236
## 124    Q29_3 ~~ Q31_1  1.911 -0.126  -0.126   -0.411   -0.411
## 125    Q29_3 ~~ Q31_2  1.134 -0.107  -0.107   -0.276   -0.276
## 126    Q29_3 ~~ Q31_3  2.036  0.145   0.145    0.404    0.404
## 127    Q29_3 ~~ Q31_4  0.011  0.012   0.012    0.040    0.040
## 128    Q29_3 ~~ Q31_5  0.043  0.024   0.024    0.040    0.040
## 129    Q29_4 ~~ Q29_5  1.885 -0.147  -0.147   -0.436   -0.436
## 130    Q29_4 ~~ Q31_6  0.545  0.070   0.070    0.232    0.232
## 131    Q29_4 ~~ Q31_1  2.890  0.153   0.153    0.801    0.801
## 132    Q29_4 ~~ Q31_2  1.348 -0.109  -0.109   -0.457   -0.457
## 133    Q29_4 ~~ Q31_3  0.140  0.048   0.048    0.216    0.216
## 134    Q29_4 ~~ Q31_4  0.093 -0.040  -0.040   -0.208   -0.208
## 135    Q29_4 ~~ Q31_5  0.041  0.028   0.028    0.076    0.076
## 136    Q29_5 ~~ Q31_6  1.085  0.106   0.106    0.202    0.202
## 137    Q29_5 ~~ Q31_1  0.356  0.059   0.059    0.176    0.176
## 138    Q29_5 ~~ Q31_2  0.518 -0.066  -0.066   -0.158   -0.158
## 139    Q29_5 ~~ Q31_3  0.640  0.113   0.113    0.293    0.293
## 140    Q29_5 ~~ Q31_4  0.322  0.068   0.068    0.202    0.202
## 141    Q29_5 ~~ Q31_5  0.387  0.085   0.085    0.131    0.131
## 142    Q31_6 ~~ Q31_1  0.471 -0.076  -0.076   -0.257   -0.257
## 143    Q31_6 ~~ Q31_2  5.835 -0.210  -0.210   -0.563   -0.563
## 144    Q31_6 ~~ Q31_3  3.958  0.195   0.195    0.565    0.565
## 145    Q31_6 ~~ Q31_4  1.214  0.107   0.107    0.356    0.356
## 146    Q31_6 ~~ Q31_5  1.687 -0.183  -0.183   -0.314   -0.314
## 147    Q31_1 ~~ Q31_2 10.154  0.266   0.266    1.126    1.126
## 148    Q31_1 ~~ Q31_3  6.355 -0.253  -0.253   -1.158   -1.158
## 149    Q31_1 ~~ Q31_4  7.905 -0.313  -0.313   -1.639   -1.639
```

```
## 150    Q31_1 ~~ Q31_5  0.997  0.109   0.109    0.295    0.295
## 151    Q31_2 ~~ Q31_3  2.691 -0.192  -0.192   -0.699   -0.699
## 152    Q31_2 ~~ Q31_4  0.003 -0.006  -0.006   -0.024   -0.024
## 153    Q31_2 ~~ Q31_5  4.633  0.241   0.241    0.520    0.520
## 154    Q31_3 ~~ Q31_4  4.709  0.185   0.185    0.829    0.829
## 155    Q31_3 ~~ Q31_5  4.046 -0.254  -0.254   -0.592   -0.592
## 156    Q31_4 ~~ Q31_5  1.178 -0.148  -0.148   -0.393   -0.393
```

```r
semPaths(fit, whatLabels = 'std', edge.color = 'black', curve = 2, residuals = FALSE,
         label.scale = TRUE, mar = c(8, 8, 8, 8))
```



With numeric data

```r
df.matched[, names(df.matched) %like% "Q29|Q31"] <- data.frame(lapply(df.matched[, names(df.matched) %li

fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q29|Q31"]))
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

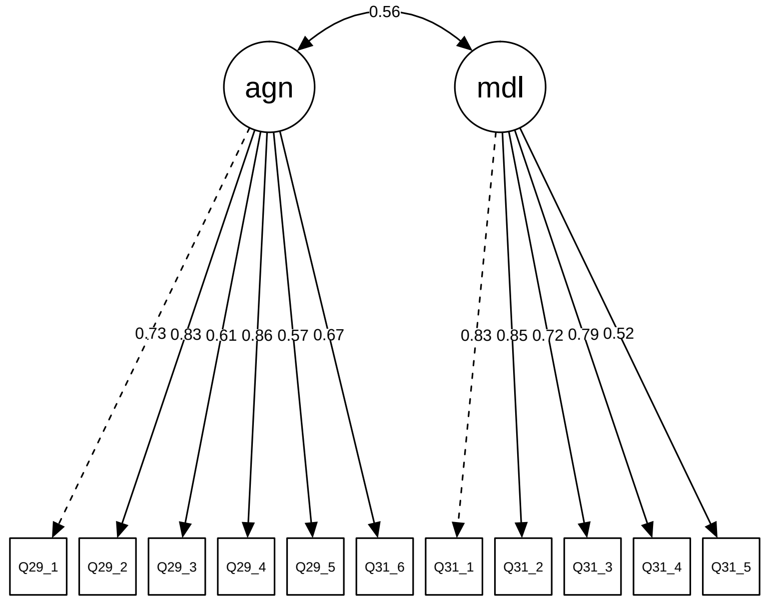
```
## lavaan 0.6-3 ended normally after 28 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         23
```

```
##
##   Number of observations                            60
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     105.260
##   Degrees of freedom                                43
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              411.011
##   Degrees of freedom                                55
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.825
##   Tucker-Lewis Index (TLI)                       0.776
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -794.558
##   Loglikelihood unrestricted model (H1)       -741.928
##
##   Number of free parameters                         23
##   Akaike (AIC)                                1635.117
##   Bayesian (BIC)                              1683.287
##   Sample-size adjusted Bayesian (BIC)         1610.946
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.155
##   90 Percent Confidence Interval          0.118  0.193
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.092
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q29_1             1.000                               0.664    0.726
##     Q29_2             1.326    0.216    6.145    0.000    0.881    0.834
##     Q29_3             1.058    0.233    4.540    0.000    0.703    0.615
##     Q29_4             1.467    0.233    6.300    0.000    0.975    0.858
##     Q29_5             0.863    0.205    4.208    0.000    0.573    0.571
##     Q31_6             1.061    0.216    4.914    0.000    0.705    0.665
```

```
##   modeling =~
##     Q31_1             1.000                               0.840    0.834
##     Q31_2             0.934    0.125    7.482    0.000    0.785    0.846
##     Q31_3             0.906    0.149    6.093    0.000    0.761    0.722
##     Q31_4             1.024    0.148    6.893    0.000    0.860    0.793
##     Q31_5             0.521    0.127    4.089    0.000    0.438    0.521
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~~
##     modeling          0.310    0.101    3.062    0.002    0.555    0.555
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.395    0.083    4.735    0.000    0.395    0.472
##    .Q29_2             0.341    0.087    3.927    0.000    0.341    0.305
##    .Q29_3             0.812    0.160    5.078    0.000    0.812    0.622
##    .Q29_4             0.340    0.095    3.590    0.000    0.340    0.264
##    .Q29_5             0.681    0.132    5.161    0.000    0.681    0.674
##    .Q31_6             0.626    0.126    4.954    0.000    0.626    0.558
##    .Q31_1             0.309    0.079    3.907    0.000    0.309    0.305
##    .Q31_2             0.245    0.065    3.748    0.000    0.245    0.284
##    .Q31_3             0.531    0.112    4.742    0.000    0.531    0.478
##    .Q31_4             0.437    0.101    4.322    0.000    0.437    0.371
##    .Q31_5             0.515    0.098    5.231    0.000    0.515    0.729
##     agency            0.441    0.141    3.130    0.002    1.000    1.000
##     modeling          0.706    0.185    3.814    0.000    1.000    1.000
##
## Modification Indices:
##
##         lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 26   agency =~ Q31_1  1.661  0.227   0.151    0.149    0.149
## 27   agency =~ Q31_2  8.779 -0.475  -0.315   -0.340   -0.340
## 28   agency =~ Q31_3  3.924  0.408   0.271    0.257    0.257
## 29   agency =~ Q31_4  0.304  0.109   0.072    0.067    0.067
## 30   agency =~ Q31_5  0.362 -0.115  -0.077   -0.091   -0.091
## 31 modeling =~ Q29_1  3.157  0.250   0.210    0.230    0.230
## 32 modeling =~ Q29_2  2.755 -0.242  -0.203   -0.192   -0.192
## 33 modeling =~ Q29_3  0.004 -0.013  -0.011   -0.009   -0.009
## 34 modeling =~ Q29_4  0.013  0.017   0.014    0.013    0.013
## 35 modeling =~ Q29_5  0.786  0.156   0.131    0.130    0.130
## 36 modeling =~ Q31_6  0.176 -0.072  -0.061   -0.057   -0.057
## 37    Q29_1 ~~ Q29_2  0.167 -0.028  -0.028   -0.075   -0.075
## 38    Q29_1 ~~ Q29_3  0.045 -0.018  -0.018   -0.031   -0.031
## 39    Q29_1 ~~ Q29_4  0.085 -0.021  -0.021   -0.058   -0.058
## 40    Q29_1 ~~ Q29_5  1.786 -0.101  -0.101   -0.194   -0.194
## 41    Q29_1 ~~ Q31_6  0.940  0.073   0.073    0.146    0.146
## 42    Q29_1 ~~ Q31_1  0.927 -0.053  -0.053   -0.153   -0.153
## 43    Q29_1 ~~ Q31_2  2.322  0.076   0.076    0.246    0.246
## 44    Q29_1 ~~ Q31_3  0.031 -0.012  -0.012   -0.026   -0.026
## 45    Q29_1 ~~ Q31_4  1.854  0.086   0.086    0.207    0.207
## 46    Q29_1 ~~ Q31_5  0.340 -0.037  -0.037   -0.082   -0.082
## 47    Q29_2 ~~ Q29_3  5.280  0.202   0.202    0.383    0.383
## 48    Q29_2 ~~ Q29_4  3.851  0.172   0.172    0.504    0.504
```

```
## 49     Q29_2 ~~ Q29_5  0.059 -0.019  -0.019   -0.039   -0.039
## 50     Q29_2 ~~ Q31_6  7.115 -0.213  -0.213   -0.460   -0.460
## 51     Q29_2 ~~ Q31_1  1.544  0.069   0.069    0.213    0.213
## 52     Q29_2 ~~ Q31_2  0.571 -0.038  -0.038   -0.132   -0.132
## 53     Q29_2 ~~ Q31_3  0.187 -0.029  -0.029   -0.068   -0.068
## 54     Q29_2 ~~ Q31_4  1.969 -0.089  -0.089   -0.231   -0.231
## 55     Q29_2 ~~ Q31_5  0.151 -0.025  -0.025   -0.059   -0.059
## 56     Q29_3 ~~ Q29_4  8.182 -0.266  -0.266   -0.506   -0.506
## 57     Q29_3 ~~ Q29_5  5.759  0.249   0.249    0.334    0.334
## 58     Q29_3 ~~ Q31_6  0.394 -0.064  -0.064   -0.090   -0.090
## 59     Q29_3 ~~ Q31_1  4.618 -0.166  -0.166   -0.330   -0.330
## 60     Q29_3 ~~ Q31_2  0.000  0.001   0.001    0.003    0.003
## 61     Q29_3 ~~ Q31_3  2.306  0.142   0.142    0.216    0.216
## 62     Q29_3 ~~ Q31_4  0.496  0.062   0.062    0.104    0.104
## 63     Q29_3 ~~ Q31_5  0.454  0.059   0.059    0.092    0.092
## 64     Q29_4 ~~ Q29_5  2.082 -0.120  -0.120   -0.249   -0.249
## 65     Q29_4 ~~ Q31_6  2.770  0.141   0.141    0.306    0.306
## 66     Q29_4 ~~ Q31_1  5.661  0.137   0.137    0.423    0.423
## 67     Q29_4 ~~ Q31_2  1.547 -0.065  -0.065   -0.225   -0.225
## 68     Q29_4 ~~ Q31_3  0.129 -0.025  -0.025   -0.059   -0.059
## 69     Q29_4 ~~ Q31_4  1.202 -0.072  -0.072   -0.187   -0.187
## 70     Q29_4 ~~ Q31_5  0.287  0.035   0.035    0.084    0.084
## 71     Q29_5 ~~ Q31_6  1.831  0.125   0.125    0.191    0.191
## 72     Q29_5 ~~ Q31_1  0.002 -0.003  -0.003   -0.006   -0.006
## 73     Q29_5 ~~ Q31_2  0.348 -0.037  -0.037   -0.092   -0.092
## 74     Q29_5 ~~ Q31_3  0.306  0.047   0.047    0.078    0.078
## 75     Q29_5 ~~ Q31_4  0.480  0.055   0.055    0.102    0.102
## 76     Q29_5 ~~ Q31_5  0.548  0.059   0.059    0.100    0.100
## 77     Q31_6 ~~ Q31_1  1.455 -0.083  -0.083   -0.187   -0.187
## 78     Q31_6 ~~ Q31_2  2.751 -0.103  -0.103   -0.262   -0.262
## 79     Q31_6 ~~ Q31_3  4.578  0.177   0.177    0.307    0.307
## 80     Q31_6 ~~ Q31_4  3.508  0.146   0.146    0.280    0.280
## 81     Q31_6 ~~ Q31_5  2.386 -0.121  -0.121   -0.213   -0.213
## 82     Q31_1 ~~ Q31_2  8.751  0.205   0.205    0.746    0.746
## 83     Q31_1 ~~ Q31_3  1.507 -0.092  -0.092   -0.226   -0.226
## 84     Q31_1 ~~ Q31_4 12.039 -0.270  -0.270   -0.734   -0.734
## 85     Q31_1 ~~ Q31_5  1.581  0.081   0.081    0.202    0.202
## 86     Q31_2 ~~ Q31_3  8.726 -0.203  -0.203   -0.563   -0.563
## 87     Q31_2 ~~ Q31_4  0.028  0.012   0.012    0.037    0.037
## 88     Q31_2 ~~ Q31_5  5.331  0.135   0.135    0.380    0.380
## 89     Q31_3 ~~ Q31_4 21.199  0.374   0.374    0.776    0.776
## 90     Q31_3 ~~ Q31_5  4.829 -0.165  -0.165   -0.316   -0.316
## 91     Q31_4 ~~ Q31_5  3.201 -0.129  -0.129   -0.271   -0.271
```

```r
semPaths(fit, whatLabels = 'std', edge.color = 'black', curve = 2, residuals = FALSE,
         label.scale = TRUE, mar = c(8, 8, 8, 8))
```



EFA

```
fa.parallel(unique(df.matched[, names(df.matched) %like% "Q29|Q31"]))
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

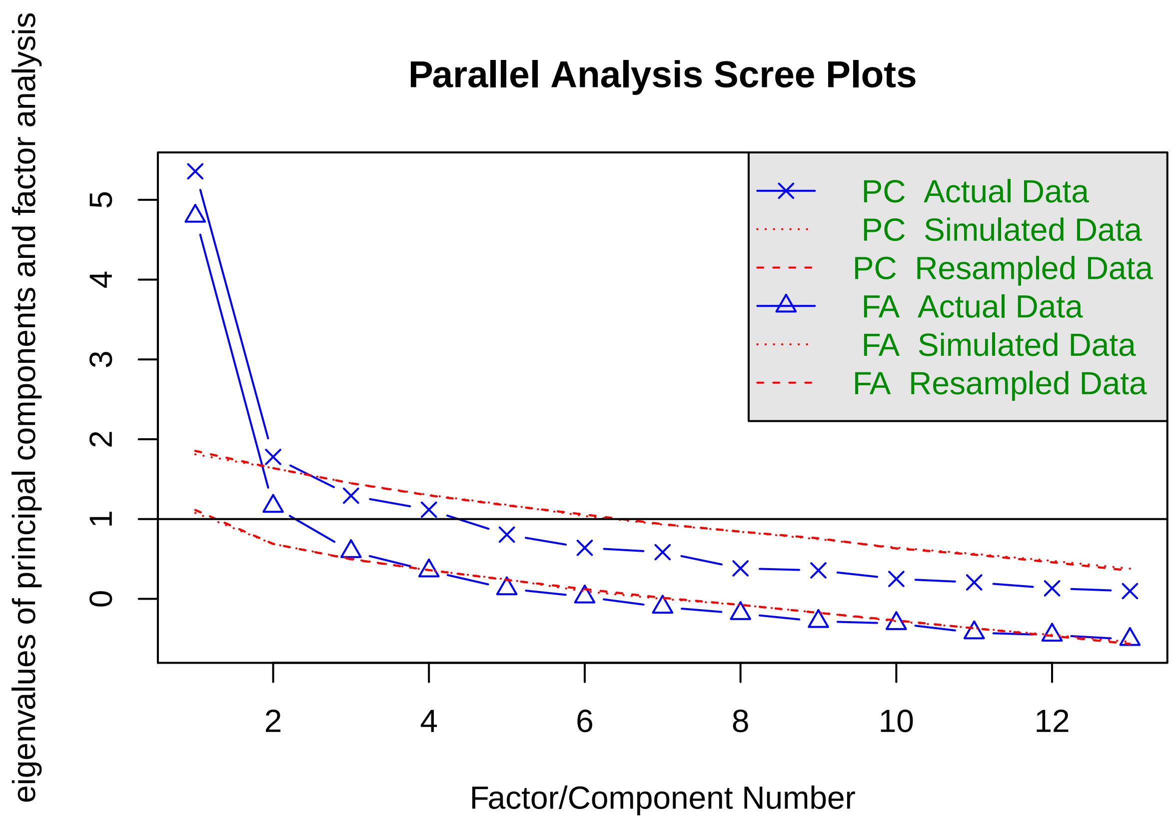
```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully
```




```
## Parallel analysis suggests that the number of factors =  2  and the number of components =  1
```

```r
fit <- fa(unique(df.matched[, names(df.matched) %like% "Q29|Q31"]), 2)
```

```
## Loading required namespace: GPArotation
```

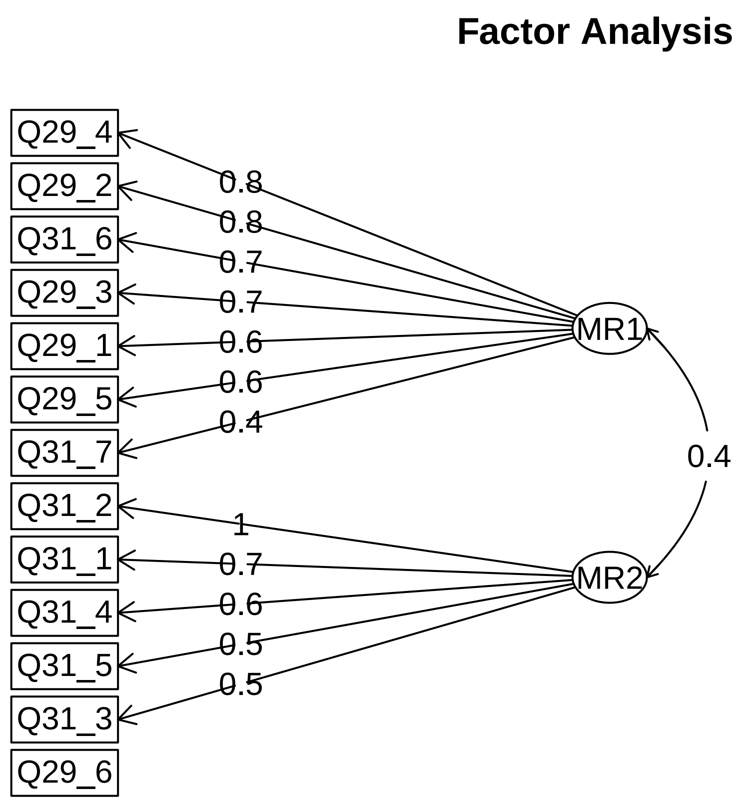
```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```r
fit
```

```
## Factor Analysis using method =  minres
## Call: fa(r = unique(df.matched[, names(df.matched) %like% "Q29|Q31"]),
##     nfactors = 2)
##
##  Warning: A Heywood case was detected.
## Standardized loadings (pattern matrix) based upon correlation matrix
##         MR1   MR2    h2    u2 com
## Q29_1  0.63  0.16 0.511 0.489 1.1
## Q29_2  0.80 -0.07 0.592 0.408 1.0
## Q29_3  0.66 -0.02 0.421 0.579 1.0
## Q29_4  0.80  0.04 0.663 0.337 1.0
## Q29_5  0.60  0.06 0.389 0.611 1.0
## Q29_6 -0.05 -0.10 0.018 0.982 1.5
## Q31_1  0.17  0.73 0.660 0.340 1.1
## Q31_2 -0.12  1.01 0.929 0.071 1.0
## Q31_3  0.43  0.47 0.570 0.430 2.0
## Q31_4  0.28  0.63 0.628 0.372 1.4
## Q31_5 -0.01  0.52 0.268 0.732 1.0
## Q31_6  0.75 -0.09 0.511 0.489 1.0
## Q31_7  0.39  0.07 0.179 0.821 1.1
##
##                        MR1  MR2
## SS loadings           3.65 2.69
## Proportion Var        0.28 0.21
## Cumulative Var        0.28 0.49
## Proportion Explained  0.58 0.42
## Cumulative Proportion 0.58 1.00
##
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.42
## MR2 0.42 1.00
##
## Mean item complexity =  1.2
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  78  and the objective function was  7.89 with Chi Squa
## The degrees of freedom for the model are 53  and the objective function was  2.32
##
## The root mean square of the residuals (RMSR) is  0.08
## The df corrected root mean square of the residuals is  0.1
##
```

```
## The harmonic number of observations is  60 with the empirical chi square  66.04  with prob <  0.11
## The total number of observations was  60  with Likelihood Chi Square =  121.84  with prob <  2.4e-07
##
## Tucker Lewis Index of factoring reliability =  0.699
## RMSEA index =  0.164  and the 90 % confidence intervals are  0.114 0.183
## BIC =  -95.16
## Fit based upon off diagonal values = 0.95
## Measures of factor score adequacy
##                                                    MR1  MR2
## Correlation of (regression) scores with factors   0.94 0.98
## Multiple R square of scores with factors          0.89 0.96
## Minimum correlation of possible factor scores     0.78 0.93
```

```
fa.diagram(fit)
```



CFA with model suggested by EFA (only minor changes that I think are theoretically justifiable)

```
mod <- '
  agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q31_6 + Q29_5
  modeling =~ Q31_1 + Q31_2 + Q31_4
'
```

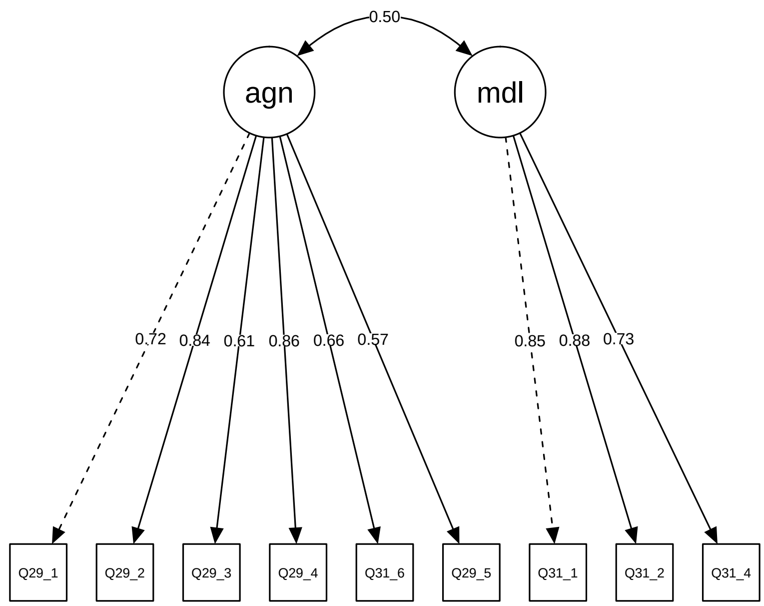
```r
fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q29|Q31"]))
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 25 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         19
##
##   Number of observations                            60
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      64.507
##   Degrees of freedom                                26
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              316.697
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.863
##   Tucker-Lewis Index (TLI)                       0.810
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -658.359
##   Loglikelihood unrestricted model (H1)       -626.106
##
##   Number of free parameters                         19
##   Akaike (AIC)                                1354.718
##   Bayesian (BIC)                              1394.511
##   Sample-size adjusted Bayesian (BIC)         1334.751
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.157
##   90 Percent Confidence Interval          0.109  0.206
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.086
##
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##   Standard Errors                             Standard
##
## Latent Variables:
```

```
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q29_1             1.000                               0.662    0.724
##     Q29_2             1.337    0.217    6.150    0.000    0.885    0.838
##     Q29_3             1.058    0.234    4.515    0.000    0.701    0.613
##     Q29_4             1.474    0.235    6.283    0.000    0.976    0.859
##     Q31_6             1.058    0.217    4.876    0.000    0.701    0.661
##     Q29_5             0.860    0.206    4.175    0.000    0.570    0.567
##   modeling =~
##     Q31_1             1.000                               0.862    0.855
##     Q31_2             0.952    0.129    7.389    0.000    0.820    0.884
##     Q31_4             0.920    0.148    6.214    0.000    0.793    0.731
##
## Covariances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~~
##     modeling          0.287    0.100    2.859    0.004    0.502    0.502
##
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.398    0.084    4.741    0.000    0.398    0.475
##    .Q29_2             0.332    0.086    3.861    0.000    0.332    0.298
##    .Q29_3             0.816    0.161    5.081    0.000    0.816    0.624
##    .Q29_4             0.337    0.095    3.555    0.000    0.337    0.261
##    .Q31_6             0.632    0.127    4.962    0.000    0.632    0.562
##    .Q29_5             0.685    0.133    5.166    0.000    0.685    0.678
##    .Q31_1             0.273    0.087    3.139    0.002    0.273    0.269
##    .Q31_2             0.189    0.073    2.588    0.010    0.189    0.219
##    .Q31_4             0.548    0.119    4.609    0.000    0.548    0.466
##     agency            0.439    0.141    3.118    0.002    1.000    1.000
##     modeling          0.742    0.192    3.860    0.000    1.000    1.000
##
## Modification Indices:
##
##         lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 22   agency =~ Q31_1  4.889  0.388   0.257    0.255    0.255
## 23   agency =~ Q31_2 10.691 -0.533  -0.353   -0.381   -0.381
## 24   agency =~ Q31_4  2.045  0.290   0.192    0.177    0.177
## 25 modeling =~ Q29_1  3.467  0.244   0.210    0.230    0.230
## 26 modeling =~ Q29_2  1.881 -0.184  -0.158   -0.150   -0.150
## 27 modeling =~ Q29_3  0.139 -0.067  -0.058   -0.051   -0.051
## 28 modeling =~ Q29_4  0.074  0.038   0.033    0.029    0.029
## 29 modeling =~ Q31_6  0.532 -0.117  -0.101   -0.095   -0.095
## 30 modeling =~ Q29_5  0.473  0.113   0.097    0.097    0.097
## 31    Q29_1 ~~ Q29_2  0.218 -0.032  -0.032   -0.087   -0.087
## 32    Q29_1 ~~ Q29_3  0.028 -0.014  -0.014   -0.025   -0.025
## 33    Q29_1 ~~ Q29_4  0.074 -0.020  -0.020   -0.054   -0.054
## 34    Q29_1 ~~ Q31_6  1.057  0.077   0.077    0.154    0.154
## 35    Q29_1 ~~ Q29_5  1.616 -0.096  -0.096   -0.185   -0.185
## 36    Q29_1 ~~ Q31_1  1.666 -0.071  -0.071   -0.214   -0.214
## 37    Q29_1 ~~ Q31_2  2.647  0.080   0.080    0.292    0.292
## 38    Q29_1 ~~ Q31_4  1.751  0.091   0.091    0.195    0.195
## 39    Q29_2 ~~ Q29_3  5.402  0.204   0.204    0.392    0.392
## 40    Q29_2 ~~ Q29_4  3.201  0.160   0.160    0.478    0.478
```

```
## 41    Q29_2 ~~ Q31_6  7.382 -0.217  -0.217   -0.474   -0.474
## 42    Q29_2 ~~ Q29_5  0.057 -0.019  -0.019   -0.039   -0.039
## 43    Q29_2 ~~ Q31_1  1.376  0.064   0.064    0.212    0.212
## 44    Q29_2 ~~ Q31_2  1.253 -0.055  -0.055   -0.219   -0.219
## 45    Q29_2 ~~ Q31_4  1.836 -0.093  -0.093   -0.217   -0.217
## 46    Q29_3 ~~ Q29_4  8.168 -0.267  -0.267   -0.508   -0.508
## 47    Q29_3 ~~ Q31_6  0.326 -0.059  -0.059   -0.082   -0.082
## 48    Q29_3 ~~ Q29_5  5.897  0.253   0.253    0.338    0.338
## 49    Q29_3 ~~ Q31_1  3.317 -0.139  -0.139   -0.293   -0.293
## 50    Q29_3 ~~ Q31_2  0.566  0.051   0.051    0.131    0.131
## 51    Q29_3 ~~ Q31_4  1.025  0.097   0.097    0.145    0.145
## 52    Q29_4 ~~ Q31_6  3.017  0.148   0.148    0.321    0.321
## 53    Q29_4 ~~ Q29_5  1.953 -0.116  -0.116   -0.242   -0.242
## 54    Q29_4 ~~ Q31_1  6.548  0.146   0.146    0.480    0.480
## 55    Q29_4 ~~ Q31_2  2.764 -0.085  -0.085   -0.338   -0.338
## 56    Q29_4 ~~ Q31_4  0.671 -0.058  -0.058   -0.136   -0.136
## 57    Q31_6 ~~ Q29_5  1.962  0.130   0.130    0.198    0.198
## 58    Q31_6 ~~ Q31_1  0.485 -0.047  -0.047   -0.113   -0.113
## 59    Q31_6 ~~ Q31_2  1.612 -0.077  -0.077   -0.223   -0.223
## 60    Q31_6 ~~ Q31_4  4.160  0.174   0.174    0.295    0.295
## 61    Q29_5 ~~ Q31_1  0.067  0.018   0.018    0.042    0.042
## 62    Q29_5 ~~ Q31_2  0.152 -0.024  -0.024   -0.067   -0.067
## 63    Q29_5 ~~ Q31_4  0.860  0.081   0.081    0.132    0.132
## 64    Q31_1 ~~ Q31_2  2.044  0.254   0.254    1.121    1.121
## 65    Q31_1 ~~ Q31_4 10.691 -0.438  -0.438   -1.132   -1.132
## 66    Q31_2 ~~ Q31_4  4.889  0.289   0.289    0.899    0.899
```

```r
semPaths(fit, whatLabels = 'std', edge.color = 'black', curve = 2, residuals = FALSE,
         label.scale = TRUE, mar = c(8, 8, 8, 8))
```



Larger SEM model with latent class variables as mediating variables in the analysis

```
df.matched <- df.matched %>%
  mutate(Lab.goal.skills = 1 * (Lab_Purpose == 'Skills'),
         Lab.goal.both = 1 * (Lab_Purpose == 'Both'),
         Lab.goal.concepts = 1 * (Lab_Purpose == 'Concepts'))

mod.sem <- '
  level: 1
    PostScores ~ PreScores
  level: 2
    agency =~ Q29_1 + Q29_2 + Q29_3 + Q29_4 + Q31_6 + Q29_5
    modeling =~ Q31_1 + Q31_2 + Q31_4

    agency ~ Lab.goal.skills + Lab.goal.both
    modeling ~ Lab.goal.skills + Lab.goal.both

    PostScores ~ agency + modeling + Lab.goal.skills + Lab.goal.both
'

fit <- sem(mod.sem, data = df.matched, cluster = "Class_ID")
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

```
## lavaan 0.6-3 ended normally after 154 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         39
##
##   Number of observations                          5018
##   Number of clusters [Class_ID]                     87
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     190.167
##   Degrees of freedom                                48
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              786.488
##   Degrees of freedom                                66
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.803
##   Tucker-Lewis Index (TLI)                       0.729
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -17217.637
##   Loglikelihood unrestricted model (H1)     -17122.553
##
##   Number of free parameters                         39
##   Akaike (AIC)                               34513.274
##   Bayesian (BIC)                             34767.584
##   Sample-size adjusted Bayesian (BIC)        34643.656
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.024
##   90 Percent Confidence Interval          0.021  0.028
##   P-value RMSEA <= 0.05                          1.000
##
## Standardized Root Mean Square Residual (corr metric):
##
##   SRMR (within covariance matrix)                0.001
##   SRMR (between covariance matrix)               0.137
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Observed information based on                Hessian
##   Standard Errors                             Standard
##
##
## Level 1 [within]:
##
```

```
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   PostScores ~
##     PreScores         0.236    0.023   10.486    0.000    0.236    0.251
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .PostScores        0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .PostScores        1.332    0.027   49.640    0.000    1.332    0.937
##
##
## Level 2 [Class_ID]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q29_1             1.000                               0.596    0.641
##     Q29_2             1.462    0.228    6.403    0.000    0.871    0.831
##     Q29_3             1.245    0.244    5.105    0.000    0.742    0.643
##     Q29_4             1.695    0.252    6.735    0.000    1.010    0.887
##     Q31_6             1.304    0.225    5.800    0.000    0.777    0.724
##     Q29_5             0.822    0.210    3.918    0.000    0.490    0.468
##   modeling =~
##     Q31_1             1.000                               0.862    0.839
##     Q31_2             1.033    0.112    9.204    0.000    0.891    0.947
##     Q31_4             0.922    0.117    7.903    0.000    0.795    0.739
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~
##     Lab.goal.sklls    1.227    0.195    6.294    0.000    2.059    1.029
##     Lab.goal.both     0.615    0.152    4.044    0.000    1.032    0.467
##   modeling ~
##     Lab.goal.sklls    0.331    0.265    1.248    0.212    0.383    0.192
##     Lab.goal.both     0.525    0.274    1.918    0.055    0.609    0.275
##   PostScores ~
##     agency            0.019    0.171    0.111    0.912    0.011    0.031
##     modeling         -0.006    0.054   -0.110    0.913   -0.005   -0.014
##     Lab.goal.sklls    0.339    0.239    1.422    0.155    0.339    0.466
##     Lab.goal.both    -0.032    0.157   -0.201    0.840   -0.032   -0.039
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             1.352    0.159    8.482    0.000    1.352    1.455
##    .Q29_2             1.765    0.168   10.521    0.000    1.765    1.684
##    .Q29_3             1.364    0.207    6.600    0.000    1.364    1.181
##    .Q29_4             1.683    0.177    9.520    0.000    1.683    1.477
##    .Q31_6             2.098    0.182   11.558    0.000    2.098    1.954
##    .Q29_5             1.770    0.188    9.398    0.000    1.770    1.691
##    .Q31_1             2.659    0.221   12.021    0.000    2.659    2.586
##    .Q31_2             2.660    0.217   12.267    0.000    2.660    2.827
```

```
##    .Q31_4             2.017    0.213    9.485    0.000    2.017    1.875
##    .PostScores        4.094    0.101   40.574    0.000    4.094   11.249
##    .agency            0.000                               0.000    0.000
##    .modeling          0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q29_1             0.508    0.083    6.139    0.000    0.508    0.588
##    .Q29_2             0.339    0.068    4.956    0.000    0.339    0.309
##    .Q29_3             0.782    0.134    5.840    0.000    0.782    0.587
##    .Q29_4             0.277    0.072    3.860    0.000    0.277    0.213
##    .Q31_6             0.549    0.094    5.833    0.000    0.549    0.476
##    .Q29_5             0.855    0.134    6.385    0.000    0.855    0.781
##    .Q31_1             0.313    0.074    4.209    0.000    0.313    0.296
##    .Q31_2             0.092    0.066    1.399    0.162    0.092    0.104
##    .Q31_4             0.525    0.095    5.508    0.000    0.525    0.454
##    .PostScores        0.097    0.025    3.915    0.000    0.097    0.735
##    .agency            0.121    0.041    2.969    0.003    0.340    0.340
##    .modeling          0.711    0.157    4.533    0.000    0.955    0.955
##
## Modification Indices:
##
##                 lhs op              rhs block group level     mi    epc
## 3         PreScores ~~        PreScores     1     1     1  0.000  0.000
## 4        PostScores ~1                      1     1     1  0.000  0.000
## 5         PreScores ~1                      1     1     1  0.000  0.000
## 35  Lab.goal.skills ~~ Lab.goal.skills     2     1     2  0.000  0.000
## 36  Lab.goal.skills ~~   Lab.goal.both     2     1     2  0.000  0.000
## 37    Lab.goal.both ~~   Lab.goal.both     2     1     2  0.000  0.000
## 48  Lab.goal.skills ~1                      2     1     2  0.000  0.000
## 49    Lab.goal.both ~1                      2     1     2  0.000  0.000
## 52        PreScores  ~       PostScores     1     1     1  0.000  0.000
## 53           agency =~            Q31_1     2     1     2  8.550  0.344
## 54           agency =~            Q31_2     2     1     2 14.856 -0.399
## 55           agency =~            Q31_4     2     1     2  9.818  0.452
## 56         modeling =~            Q29_1     2     1     2  9.347  0.292
## 57         modeling =~            Q29_2     2     1     2  0.000  0.000
## 58         modeling =~            Q29_3     2     1     2  0.508  0.084
## 59         modeling =~            Q29_4     2     1     2  0.131  0.030
## 60         modeling =~            Q31_6     2     1     2  2.149 -0.148
## 61         modeling =~            Q29_5     2     1     2  1.987  0.171
## 62            Q29_1 ~~            Q29_2     2     1     2  0.007 -0.004
## 63            Q29_1 ~~            Q29_3     2     1     2  0.565 -0.055
## 64            Q29_1 ~~            Q29_4     2     1     2  1.581  0.069
## 65            Q29_1 ~~            Q31_6     2     1     2  1.236  0.070
## 66            Q29_1 ~~            Q29_5     2     1     2  1.828 -0.101
## 67            Q29_1 ~~            Q31_1     2     1     2  0.915 -0.047
## 68            Q29_1 ~~            Q31_2     2     1     2  3.359  0.074
## 69            Q29_1 ~~            Q31_4     2     1     2  0.743  0.052
## 70            Q29_1 ~~       PostScores     2     1     2  2.029 -0.046
## 71            Q29_2 ~~            Q29_3     2     1     2  7.516  0.183
## 72            Q29_2 ~~            Q29_4     2     1     2  2.746  0.099
## 73            Q29_2 ~~            Q31_6     2     1     2  5.024 -0.132
## 74            Q29_2 ~~            Q29_5     2     1     2  1.039  0.068
```

```
## 75            Q29_2 ~~            Q31_1     2     1     2  4.440   0.090
## 76            Q29_2 ~~            Q31_2     2     1     2  0.729  -0.030
## 77            Q29_2 ~~            Q31_4     2     1     2  1.499  -0.065
## 78            Q29_2 ~~       PostScores     2     1     2  8.798  -0.086
## 79            Q29_3 ~~            Q29_4     2     1     2 17.693  -0.288
## 80            Q29_3 ~~            Q31_6     2     1     2  2.364  -0.120
## 81            Q29_3 ~~            Q29_5     2     1     2  9.381   0.283
## 82            Q29_3 ~~            Q31_1     2     1     2  4.004  -0.121
## 83            Q29_3 ~~            Q31_2     2     1     2  1.904   0.069
## 84            Q29_3 ~~            Q31_4     2     1     2  0.339   0.043
## 85            Q29_3 ~~       PostScores     2     1     2  7.086  -0.106
## 86            Q29_4 ~~            Q31_6     2     1     2  0.839   0.056
## 87            Q29_4 ~~            Q29_5     2     1     2  3.201  -0.120
## 88            Q29_4 ~~            Q31_1     2     1     2  9.838   0.132
## 89            Q29_4 ~~            Q31_2     2     1     2  2.310  -0.053
## 90            Q29_4 ~~            Q31_4     2     1     2  0.787  -0.046
## 91            Q29_4 ~~       PostScores     2     1     2 12.493   0.105
## 92            Q31_6 ~~            Q29_5     2     1     2  0.649   0.064
## 93            Q31_6 ~~            Q31_1     2     1     2  1.329  -0.059
## 94            Q31_6 ~~            Q31_2     2     1     2  1.590  -0.054
## 95            Q31_6 ~~            Q31_4     2     1     2  4.513   0.135
## 96            Q31_6 ~~       PostScores     2     1     2  2.126   0.050
## 97            Q29_5 ~~            Q31_1     2     1     2  0.097  -0.019
## 98            Q29_5 ~~            Q31_2     2     1     2  0.544  -0.038
## 99            Q29_5 ~~            Q31_4     2     1     2  7.069   0.203
## 100           Q29_5 ~~       PostScores     2     1     2  1.015   0.041
## 101           Q31_1 ~~            Q31_2     2     1     2  4.243   0.756
## 102           Q31_1 ~~            Q31_4     2     1     2  0.001  -0.006
## 103           Q31_1 ~~       PostScores     2     1     2  1.043  -0.027
## 104           Q31_2 ~~            Q31_4     2     1     2  2.345  -0.394
## 105           Q31_2 ~~       PostScores     2     1     2  1.569   0.030
## 106           Q31_4 ~~       PostScores     2     1     2  0.310  -0.018
## 107          agency ~~         modeling     2     1     2  4.008   0.076
## 108          agency  ~         modeling     2     1     2  4.008   0.107
## 109          agency  ~       PostScores     2     1     2  3.448 -16.611
## 110        modeling  ~           agency     2     1     2  3.996   0.626
## 111        modeling  ~       PostScores     2     1     2  6.510  42.287
## 112 Lab.goal.skills  ~           agency     2     1     2  0.000   0.000
## 113 Lab.goal.skills  ~         modeling     2     1     2  0.000  -0.001
## 114 Lab.goal.skills  ~       PostScores     2     1     2  0.000   0.000
## 115 Lab.goal.skills  ~    Lab.goal.both     2     1     2  0.000   0.000
## 116   Lab.goal.both  ~           agency     2     1     2  0.000   0.000
## 117   Lab.goal.both  ~         modeling     2     1     2  0.000   0.000
## 118   Lab.goal.both  ~       PostScores     2     1     2  0.000   0.000
## 119   Lab.goal.both  ~ Lab.goal.skills     2     1     2  0.000   0.000
##     sepc.lv sepc.all sepc.nox
## 3     0.000    0.000    0.000
## 4     0.000    0.000    0.000
## 5     0.000    0.000    0.000
## 35    0.000    0.000    0.000
## 36    0.000       NA    0.000
## 37    0.000    0.000    0.000
## 48    0.000    0.000    0.000
## 49    0.000    0.000    0.000
```

```
## 52    0.000    0.000    0.000
## 53    0.205    0.200    0.200
## 54   -0.238   -0.253   -0.253
## 55    0.269    0.250    0.250
## 56    0.252    0.271    0.271
## 57    0.000    0.000    0.000
## 58    0.073    0.063    0.063
## 59    0.026    0.023    0.023
## 60   -0.128   -0.119   -0.119
## 61    0.148    0.141    0.141
## 62   -0.004   -0.010   -0.010
## 63   -0.055   -0.087   -0.087
## 64    0.069    0.185    0.185
## 65    0.070    0.132    0.132
## 66   -0.101   -0.153   -0.153
## 67   -0.047   -0.117   -0.117
## 68    0.074    0.343    0.343
## 69    0.052    0.100    0.100
## 70   -0.046   -0.205   -0.205
## 71    0.183    0.356    0.356
## 72    0.099    0.322    0.322
## 73   -0.132   -0.305   -0.305
## 74    0.068    0.126    0.126
## 75    0.090    0.277    0.277
## 76   -0.030   -0.172   -0.172
## 77   -0.065   -0.153   -0.153
## 78   -0.086   -0.475   -0.475
## 79   -0.288   -0.619   -0.619
## 80   -0.120   -0.183   -0.183
## 81    0.283    0.346    0.346
## 82   -0.121   -0.244   -0.244
## 83    0.069    0.259    0.259
## 84    0.043    0.068    0.068
## 85   -0.106   -0.383   -0.383
## 86    0.056    0.144    0.144
## 87   -0.120   -0.247   -0.247
## 88    0.132    0.449    0.449
## 89   -0.053   -0.334   -0.334
## 90   -0.046   -0.121   -0.121
## 91    0.105    0.642    0.642
## 92    0.064    0.093    0.093
## 93   -0.059   -0.143   -0.143
## 94   -0.054   -0.241   -0.241
## 95    0.135    0.251    0.251
## 96    0.050    0.215    0.215
## 97   -0.019   -0.037   -0.037
## 98   -0.038   -0.136   -0.136
## 99    0.203    0.303    0.303
## 100   0.041    0.141    0.141
## 101   0.756    4.458    4.458
## 102  -0.006   -0.015   -0.015
## 103  -0.027   -0.157   -0.157
## 104  -0.394   -1.795   -1.795
## 105   0.030    0.319    0.319
```

```
## 106  -0.018   -0.081   -0.081
## 107   0.259    0.259    0.259
## 108   0.154    0.154    0.154
## 109 -27.870  -10.144  -10.144
## 110   0.433    0.433    0.433
## 111  49.029   17.844   17.844
## 112   0.000    0.000    0.000
## 113  -0.001   -0.001   -0.001
## 114   0.000    0.000    0.000
## 115   0.000    0.000    0.000
## 116   0.000    0.000    0.000
## 117   0.000   -0.001   -0.001
## 118   0.000    0.000    0.000
## 119   0.000    0.000    0.000
```