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))
```

Scoring/cleaning functions

```
Read.Score <- function(file){
  dt <- fread(file)
  answers.cols <- names(dt)[grep('(a|b)$', names(dt))]

  dt[, (answers.cols) := lapply(.SD, function(x) case_when(x == 5 ~ 1,
                                                             x == 1 ~ -1,
                                                             TRUE ~ 0)),
     .SDcols = answers.cols]
  df <- dt[, -c('q40a', 'q40b')]

  df$student.score <- rowSums(df %>% select(grep("a$", names(.))))
  df$expert.score <- rowSums(df %>% select(grep("b$", names(.))))

  return(df)
}

Read.duplicate.cis <- function(file){
  cis.df <- read.csv(file)

  cis.noInfo <- cis.df[(cis.df$Q33 == '') | is.na(cis.df$Q33),]
  cis.FullInfo <- cis.df[(cis.df$Q33 != '') & !is.na(cis.df$Q33),]

  original.cols <- c('Q5', 'Q52',   'Q53', 'Q27', 'Q6', 'Q11', 'Q19',   'Q20', 'StartDate',
                     'anon_instructor_id', 'ResponseId', 'pre_survey_id', 'post_survey_id')

  cis.noInfo <- left_join(cis.noInfo, cis.FullInfo,
                          by = c('anon_university_id', 'Q18'),
                          suffix = c('.original', '.copy')) %>%
    select(anon_university_id, Q18, Q15.copy,   Q21.copy,   Q22_1.copy, Q22_2.copy, Q23.copy,
           Q29.copy, grep('Q(3|4)\\d_?\\d?\\.copy', names(.)),
           paste(original.cols, '.original', sep = '')) %>%
```

```
    filter(!duplicated(ResponseId.original) & !is.na(ResponseId.original)) %>%
    `colnames<-`(unlist(lapply(names(.), function (x) strsplit(x, '\\.')[[1]][1])))

  cis.df <- rbind(cis.FullInfo, cis.noInfo[, names(cis.df)])
  return(cis.df)
}
```

Read, score, and match

```
#cis.df <- Read.duplicate.cis('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_cis.c

cis.df <- read.csv('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_cis_CW.csv')

pre.df <- Read.Score('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_pre.csv')

cis.pre.df <- right_join(cis.df, pre.df, by = c('pre_survey_id' = 'survey_id'))
```

```
## Warning: Column `pre_survey_id`/`survey_id` joining factor and character
## vector, coercing into character vector
```

```
post.df <- Read.Score('C:/Users/Cole/Documents/GRA_Summer2020/eclass-public-analysis/anon_post.csv')

full.df <- full_join(cis.pre.df, post.df,
                     by = c('post_survey_id' = 'survey_id',
                            'anon_student_id'), suffix = c('.pre', '.post')) %>%
    mutate(Lab.goal = case_when(
      Q33 == 'Reinforce physics concepts.' ~ 'Concepts',
      Q33 == 'Both about equally.' ~ 'Both',
      Q33 == 'Develop lab skills.' ~ 'Skills',
      TRUE ~ NA_character_
    ),
    Lab.level = case_when(
      Q18 == 'Beyond the first year lab' ~ 'BFY',
      Q27 == 'Calculus-based' ~ 'FY.Calc',
      Q27 == 'Algebra-based' ~ 'FY.Alg',
      TRUE ~ NA_character_
    ))
```

```
## Warning: Column `post_survey_id`/`survey_id` joining factor and character
## vector, coercing into character vector
```

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

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

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

```
## [1] 55534
```

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

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

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

```
## [1] 491
```

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

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

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

```
## [1] 112
```

```r
# Remove whole classes without goal and/or level information
full.df <- data.table(full.df)[, `:=`(N.students = .N,
                                      pre.rate = sum(!is.na(student.score.pre))/.N,
                                      post.rate = sum(!is.na(student.score.post))/.N),
                               .(ResponseId)]

full.df <- full.df %>%
  filter(!is.na(Lab.goal) & !is.na(Lab.level) & (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] 32667
```

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

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

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

```
## [1] 380
```

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

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

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

```
## [1] 96
```

```r
df.matched <- full.df %>%
  filter(!is.na(student.score.pre) & !is.na(student.score.post))

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

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

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

```
## [1] 20949
```

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

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

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

```
## [1] 380
```

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

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

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

```
## [1] 96
```

```r
table(df.matched[!duplicated(df.matched$anon_university_id),]$Q15, exclude = NULL)
```

```
##
##                                                 2 year college
##                             0                                3
##                4 year college Master's granting institution
##                            47                                9
##      PhD granting institution
##                            37
```

```r
table(df.matched[!duplicated(df.matched$ResponseId),]$Lab.level, exclude = NULL)
```

```
##
##     BFY  FY.Alg FY.Calc
##     150      80     150
```

```r
table(df.matched[!duplicated(df.matched$ResponseId),]$Lab.goal, exclude = NULL)
```

```
##
##     Both Concepts   Skills
##      203       55      122
```

```r
colSums(df.matched[, c('Q52_1', 'Q52_5')], na.rm = TRUE)
```

```
## Q52_1 Q52_5
##   171   160
```

Data processing

```r
# Replace declared major with intended major in cases where students intend to switch
df.matched[is.na(df.matched$Q48) | (df.matched$Q48 == 0),
'Q48'] <- df.matched[is.na(df.matched$Q48) | (df.matched$Q48 == 0), 'Q47']

df.matched <- df.matched %>%
  mutate(Major = case_when(
    Q48 == 1 ~ 'Physics',
    Q48 == 2 ~ 'Chemistry',
    Q48 == 3 ~ 'Biochemistry',
    Q48 == 4 ~ 'Biology',
    Q48 == 5 ~ 'Engineering',
    Q48 == 6 ~ 'Engineering Physics',
    Q48 == 7 ~ 'Astronomy',
    Q48 == 8 ~ 'Astrophysics',
    Q48 == 9 ~ 'Geology/geophysics',
    Q48 == 10 ~ 'Math/applied math',
    Q48 == 11 ~ 'Computer science',
    Q48 == 12 ~ 'Physiology',
    Q48 == 13 ~ 'Other science',
    Q48 == 14 ~ 'Non-science',
    Q48 == 15 ~ 'Open/undeclared',
    TRUE ~ 'Unknown'
  ),
  Gender = case_when(
    Q54 == 1 ~ 'Woman',
    Q54 == 2 ~ 'Man',
    Q54 == 3 ~ 'Other',
    TRUE ~ 'Unknown'
  )) %>%
  mutate(Major = case_when(
    (Major == 'Physics') | (Major == 'Engineering Physics') | (Major == 'Astronomy') |
      (Major == 'Astrophysics') ~ 'Physics',
    (Major == 'Chemistry') | (Major == 'Biochemistry') | (Major == 'Biology') |
      (Major == 'Physiology') ~ 'Chem.LifeSci',
    Major == 'Engineering' ~ 'Engineering',
    (Major == 'Math/applied math') | (Major == 'Computer science') ~ 'Math.CS',
    (Major == 'Geology/geophysics') | (Major == 'Other science') ~ 'OtherSci',
```

```
    Major == 'Non-science' ~ 'NonSci',
    Major == 'Open/undeclared' ~ 'Undeclared',
    Major == 'Unknown' ~ 'Unknown',
    TRUE ~ NA_character_
  )) %>%
  mutate(Major = relevel(as.factor(Major), ref = 'Physics'),
         Gender = relevel(as.factor(Gender), ref = 'Man'),
         Lab.goal = relevel(as.factor(Lab.goal), ref = 'Concepts'),
         Lab.level = relevel(as.factor(Lab.level), ref = 'FY.Alg'))

df.matched$Race.ethnicity.Native = relevel(factor(ifelse((df.matched$Q52_5 == 1) |
                                                   (df.matched$Q52_1 == 1), 1, 0),
                                                 levels = c(1, 0)), ref = '0')
new.race.cols <- c('Race.ethnicity.Other', 'Race.ethnicity.Black',
                 'Race.ethnicity.Hispanic', 'Race.ethnicity.Asian',
                 'Race.ethnicity.White', 'Race.ethnicity.Unknown')
setnames(df.matched, old = c('Q52_7', 'Q52_3', 'Q52_4', 'Q52_2', 'Q52_6',
                           'race_unknown'), new = new.race.cols)
df.matched[is.na(df.matched)] <- 0
df.matched[new.race.cols] <- lapply(df.matched[new.race.cols], factor, levels = c(1, 0))
df.matched[new.race.cols] <- lapply(df.matched[new.race.cols], 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.goal))
    }
  } else {
    for(col in Race.ethnicity.cols){
      print(col)
      print(table(df[, col]))
    }
  }
}

table(df.matched$Gender)
```

```
##
##     Man   Other Unknown   Woman
##   12203     241     474    8031
```

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

```
## [1] "Race.ethnicity.Asian"
##
##     0     1
```

```
## 16560  4389
## [1] "Race.ethnicity.Black"
##
##     0     1
## 19826  1123
## [1] "Race.ethnicity.Hispanic"
##
##     0     1
## 19357  1592
## [1] "Race.ethnicity.White"
##
##     0     1
## 10255 10694
## [1] "Race.ethnicity.Other"
##
##     0     1
## 20482   467
## [1] "Race.ethnicity.Unknown"
##
##     0     1
## 17095  3854
## [1] "Race.ethnicity.Native"
##
##     0     1
## 20631   318
```

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

```
##
##      Physics Chem.LifeSci  Engineering      Math.CS       NonSci
##         3610         4099         6487         2696         1434
##     OtherSci   Undeclared      Unknown
##         2084          455           84
```

```
table(df.matched$Lab.goal)
```

```
##
## Concepts     Both   Skills
##     3821    11961     5167
```

```
table(df.matched$Gender, df.matched$Lab.goal)
```

```
##
##           Concepts Both Skills
##   Man         1932 7146   3125
##   Other         39  138     64
##   Unknown      103  276     95
##   Woman       1747 4401   1883
```

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

```
## [1] "Race.ethnicity.Asian"
##
##     Concepts Both Skills
##   0     3199 9101   4260
##   1      622 2860    907
## [1] "Race.ethnicity.Black"
##
##     Concepts  Both Skills
##   0     3278 11503   5045
##   1      543   458    122
## [1] "Race.ethnicity.Hispanic"
##
##     Concepts  Both Skills
##   0     3534 11086   4737
##   1      287   875    430
## [1] "Race.ethnicity.White"
##
##     Concepts Both Skills
##   0     2018 6155   2082
##   1     1803 5806   3085
## [1] "Race.ethnicity.Other"
##
##     Concepts  Both Skills
##   0     3744 11678   5060
##   1       77   283    107
## [1] "Race.ethnicity.Unknown"
##
##     Concepts Both Skills
##   0     3101 9594   4400
##   1      720 2367    767
## [1] "Race.ethnicity.Native"
##
##     Concepts  Both Skills
##   0     3777 11743   5111
##   1       44   218     56
```

```
table(df.matched$Major, df.matched$Lab.goal)
```

```
##
##                Concepts Both Skills
##   Physics           369 1950   1291
##   Chem.LifeSci      621 2690    788
##   Engineering      1541 3454   1492
##   Math.CS           500 1550    646
##   NonSci            331  752    351
##   OtherSci          349 1215    520
##   Undeclared         95  302     58
##   Unknown            15   48     21
```

```
chisq.test(df.matched[!duplicated(df.matched$ResponseId), 'Lab.goal'],
           df.matched[!duplicated(df.matched$ResponseId), 'Lab.level'])
```

```
##
```

```
##  Pearson's Chi-squared test
##
## data:  df.matched[!duplicated(df.matched$ResponseId), "Lab.goal"] and df.matched[!duplicated(df.matc
## X-squared = 42.645, df = 4, p-value = 1.226e-08
```

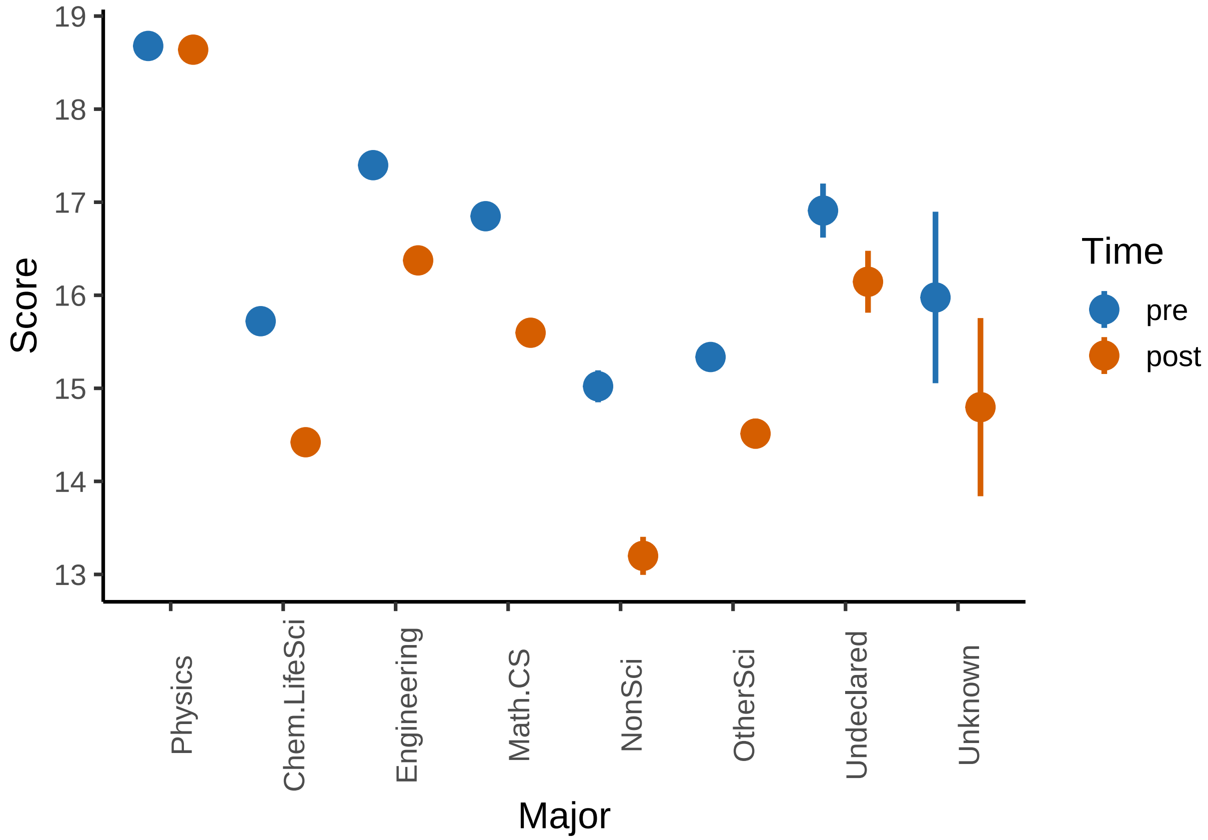
```r
summary(aov(student.score.pre ~ Lab.goal, df.matched))
```

```
##                Df Sum Sq Mean Sq F value   Pr(>F)
## Lab.goal        2   2112  1055.8    25.3 1.06e-11 ***
## Residuals   20946 874034    41.7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Descriptive statistics

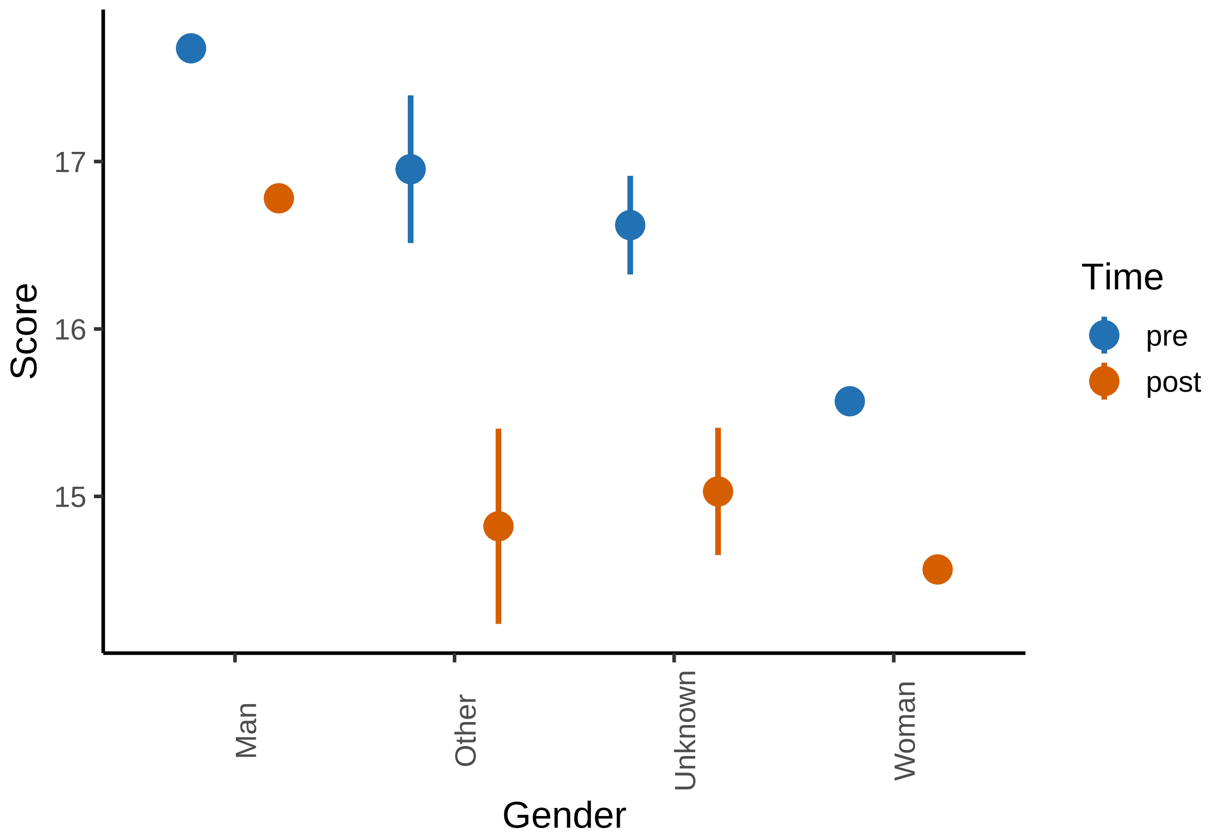
```r
plot.pre.post <- function(df, var){
  if(var == 'Race.ethnicity'){
    print(colSums(sapply(df[, c('Race.ethnicity.Native', new.race.cols)],
                         function (x) as.numeric(as.character(x)))))

    df.long <- reshape2::melt(df.matched, id.vars = c('Race.ethnicity.Native',
                                                      new.race.cols),
                              measure.vars = c('student.score.pre', 'student.score.post'),
                              variable.name = 'Time', value.name = 'Score') %>%
      reshape2::melt(., measure.vars = c('Race.ethnicity.Native', new.race.cols),
                     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('student.score.pre',
                                                   'student.score.post'),
                              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 Chem.LifeSci  Engineering      Math.CS       NonSci
##         3610         4099         6487         2696         1434
##     OtherSci   Undeclared      Unknown
##         2084          455           84
```



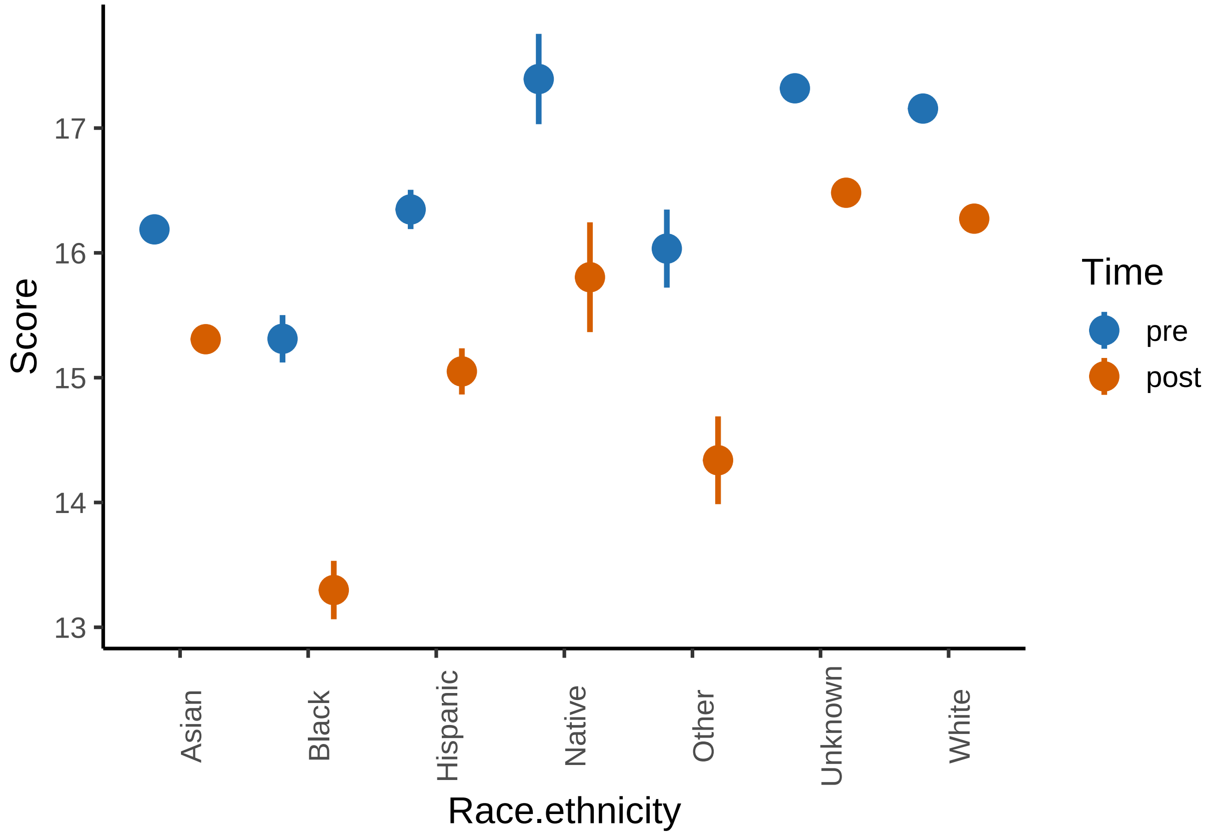

```r
plot.pre.post(df.matched, 'Gender')
```

```
##
##     Man    Other Unknown    Woman
##   12203      241     474     8031
```



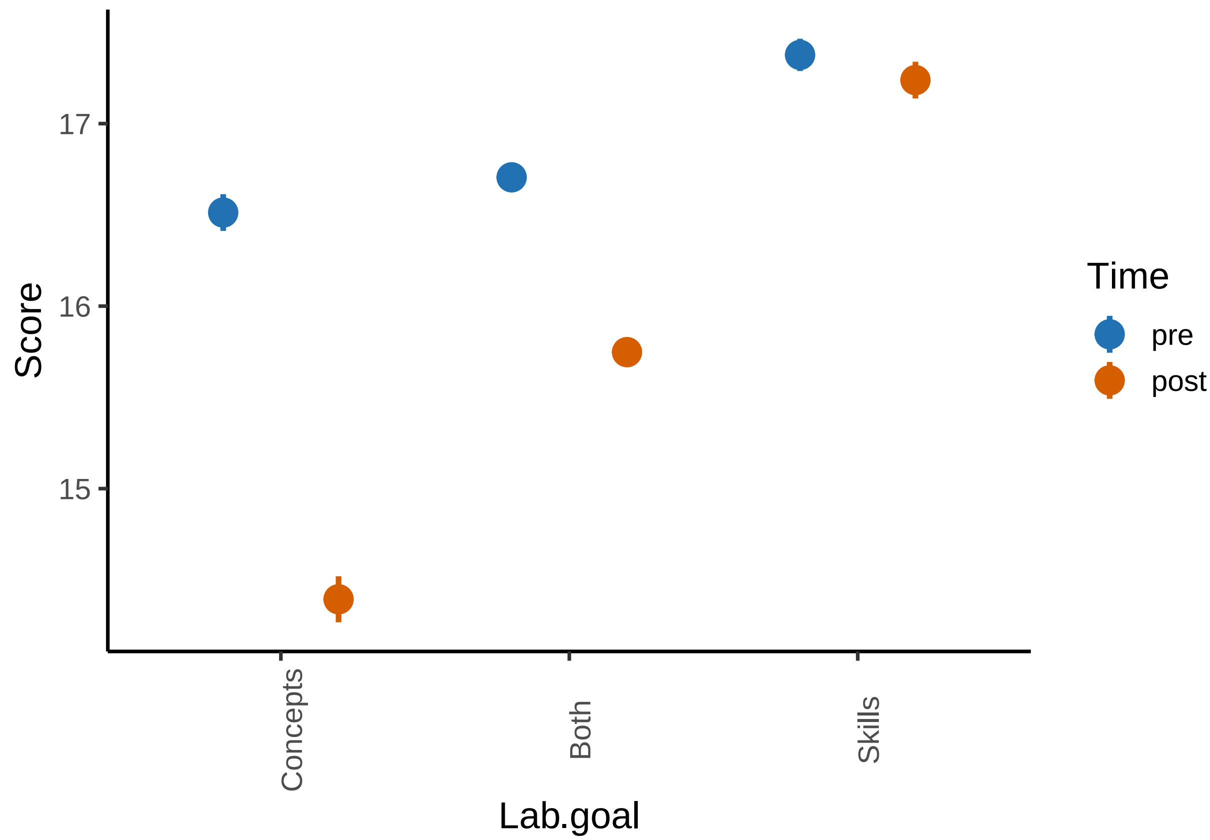

```
plot.pre.post(df.matched, 'Race.ethnicity')
```

```
##    Race.ethnicity.Native     Race.ethnicity.Other     Race.ethnicity.Black
##                      318                      467                     1123
## Race.ethnicity.Hispanic      Race.ethnicity.Asian     Race.ethnicity.White
##                     1592                     4389                    10694
##   Race.ethnicity.Unknown
##                     3854
```




```
plot.pre.post(df.matched, 'Lab.goal')
```

```
##
## Concepts      Both    Skills
##      3821     11961      5167
```



Mixed-effects models

```
mod0 <- lmer(student.score.post ~ (1 | ResponseId), df.matched)
r2(mod0)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | ResponseId student.score.post ~ 1 NA
##
##    Marginal R2: 0.000
## Conditional R2: 0.124
```

```
mod1 <- lmer(student.score.post ~ student.score.pre + Lab.goal + Lab.level + Major +
               Gender + Race.ethnicity.Native + Race.ethnicity.Other +
               Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
               Race.ethnicity.White + Race.ethnicity.Unknown + (1 | ResponseId),
             df.matched)
summary(mod1)
```

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

```
## lmerModLmerTest]
## Formula: student.score.post ~ student.score.pre + Lab.goal + Lab.level +
##     Major + Gender + Race.ethnicity.Native + Race.ethnicity.Other +
##     Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##     Race.ethnicity.White + Race.ethnicity.Unknown + (1 | ResponseId)
##    Data: df.matched
##
## REML criterion at convergence: 132224.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.3975 -0.5194  0.1195  0.6565  4.0090
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  ResponseId (Intercept)  2.026   1.423
##  Residual               31.609   5.622
## Number of obs: 20949, groups:  ResponseId, 380
##
## Fixed effects:
##                            Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)               4.098e+00  3.880e-01  6.437e+02  10.563  < 2e-16
## student.score.pre         7.079e-01  6.338e-03  2.093e+04 111.705  < 2e-16
## Lab.goalBoth              9.079e-01  2.767e-01  2.339e+02   3.281 0.001192
## Lab.goalSkills            1.627e+00  3.126e-01  2.528e+02   5.206 3.99e-07
## Lab.levelBFY              8.340e-01  2.955e-01  4.348e+02   2.822 0.004985
## Lab.levelFY.Calc          7.381e-03  2.524e-01  2.621e+02   0.029 0.976690
## MajorChem.LifeSci        -1.494e+00  1.727e-01  1.595e+04  -8.651  < 2e-16
## MajorEngineering         -7.394e-01  1.511e-01  1.798e+04  -4.894 9.97e-07
## MajorMath.CS             -1.245e+00  1.693e-01  1.988e+04  -7.352 2.03e-13
## MajorNonSci              -2.174e+00  2.098e-01  1.930e+04 -10.361  < 2e-16
## MajorOtherSci            -1.204e+00  1.930e-01  1.754e+04  -6.235 4.62e-10
## MajorUndeclared          -5.978e-01  3.001e-01  2.083e+04  -1.992 0.046422
## MajorUnknown             -1.411e+00  6.391e-01  2.090e+04  -2.208 0.027280
## GenderOther              -1.358e+00  3.717e-01  2.087e+04  -3.655 0.000258
## GenderUnknown            -6.109e-01  2.794e-01  2.092e+04  -2.187 0.028775
## GenderWoman              -3.122e-01  8.699e-02  2.092e+04  -3.589 0.000332
## Race.ethnicity.Native1   -2.373e-01  3.208e-01  2.076e+04  -0.740 0.459451
## Race.ethnicity.Other1    -7.453e-01  2.936e-01  2.077e+04  -2.539 0.011137
## Race.ethnicity.Black1    -5.918e-01  2.304e-01  1.942e+04  -2.569 0.010215
## Race.ethnicity.Hispanic1 -2.565e-01  1.906e-01  2.089e+04  -1.346 0.178286
## Race.ethnicity.Asian1     2.316e-01  1.708e-01  2.091e+04   1.357 0.174940
## Race.ethnicity.White1     7.739e-02  1.641e-01  2.084e+04   0.472 0.637185
## Race.ethnicity.Unknown1  -9.061e-02  2.028e-01  2.066e+04  -0.447 0.655072
##
## (Intercept)              ***
## student.score.pre        ***
## Lab.goalBoth             **
## Lab.goalSkills           ***
## Lab.levelBFY             **
## Lab.levelFY.Calc
## MajorChem.LifeSci        ***
## MajorEngineering         ***
## MajorMath.CS             ***
```

```
## MajorNonSci              ***
## MajorOtherSci            ***
## MajorUndeclared          *
## MajorUnknown             *
## GenderOther              ***
## GenderUnknown            *
## GenderWoman              ***
## Race.ethnicity.Native1
## Race.ethnicity.Other1    *
## Race.ethnicity.Black1    *
## Race.ethnicity.Hispanic1
## Race.ethnicity.Asian1
## Race.ethnicity.White1
## Race.ethnicity.Unknown1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 23 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
mod2 <- lmer(student.score.post ~ student.score.pre + Lab.level + Lab.goal *
               (Gender + Race.ethnicity.Native + Race.ethnicity.Other +
                  Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
                  Race.ethnicity.White + Race.ethnicity.Unknown) + Major +
               (1 | ResponseId), df.matched)
summary(mod2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: student.score.post ~ student.score.pre + Lab.level + Lab.goal *
##     (Gender + Race.ethnicity.Native + Race.ethnicity.Other +
##         Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##         Race.ethnicity.White + Race.ethnicity.Unknown) + Major +
##     (1 | ResponseId)
##    Data: df.matched
##
## REML criterion at convergence: 132171.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.3701 -0.5208  0.1210  0.6548  4.0204
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  ResponseId (Intercept)  2.012   1.418
##  Residual               31.572   5.619
## Number of obs: 20949, groups:  ResponseId, 380
##
## Fixed effects:
##                                             Estimate Std. Error         df
## (Intercept)                                4.338e+00  5.289e-01  2.105e+03
```

```
## student.score.pre                          7.082e-01  6.339e-03  2.091e+04
## Lab.levelBFY                               8.690e-01  2.954e-01  4.356e+02
## Lab.levelFY.Calc                           1.970e-02  2.522e-01  2.620e+02
## Lab.goalBoth                               6.341e-01  5.264e-01  2.824e+03
## Lab.goalSkills                             1.203e+00  6.187e-01  3.435e+03
## GenderOther                               -1.873e+00  9.263e-01  2.076e+04
## GenderUnknown                             -1.374e+00  6.053e-01  2.089e+04
## GenderWoman                               -1.107e+00  1.940e-01  2.089e+04
## Race.ethnicity.Native1                    -1.461e+00  8.603e-01  2.077e+04
## Race.ethnicity.Other1                     -9.144e-01  7.078e-01  2.071e+04
## Race.ethnicity.Black1                     -1.971e-01  4.556e-01  1.532e+04
## Race.ethnicity.Hispanic1                  -1.482e-01  4.358e-01  2.079e+04
## Race.ethnicity.Asian1                      7.637e-01  4.097e-01  2.089e+04
## Race.ethnicity.White1                      1.360e-02  3.847e-01  2.084e+04
## Race.ethnicity.Unknown1                    4.238e-02  4.724e-01  2.062e+04
## MajorChem.LifeSci                         -1.492e+00  1.726e-01  1.590e+04
## MajorEngineering                          -7.370e-01  1.511e-01  1.797e+04
## MajorMath.CS                              -1.250e+00  1.692e-01  1.986e+04
## MajorNonSci                               -2.195e+00  2.098e-01  1.927e+04
## MajorOtherSci                             -1.215e+00  1.930e-01  1.749e+04
## MajorUndeclared                           -5.925e-01  3.000e-01  2.081e+04
## MajorUnknown                              -1.405e+00  6.390e-01  2.088e+04
## Lab.goalBoth:GenderOther                   3.601e-01  1.048e+00  2.078e+04
## Lab.goalSkills:GenderOther                 1.051e+00  1.175e+00  2.082e+04
## Lab.goalBoth:GenderUnknown                 1.154e+00  7.024e-01  2.089e+04
## Lab.goalSkills:GenderUnknown               2.884e-01  8.587e-01  2.091e+04
## Lab.goalBoth:GenderWoman                   8.939e-01  2.241e-01  2.085e+04
## Lab.goalSkills:GenderWoman                 1.190e+00  2.599e-01  2.064e+04
## Lab.goalBoth:Race.ethnicity.Native1        1.119e+00  9.437e-01  2.076e+04
## Lab.goalSkills:Race.ethnicity.Native1      2.584e+00  1.151e+00  2.079e+04
## Lab.goalBoth:Race.ethnicity.Other1         1.173e-01  8.026e-01  2.072e+04
## Lab.goalSkills:Race.ethnicity.Other1       4.853e-01  9.410e-01  2.072e+04
## Lab.goalBoth:Race.ethnicity.Black1        -7.772e-01  5.537e-01  1.798e+04
## Lab.goalSkills:Race.ethnicity.Black1       1.580e-01  7.285e-01  1.999e+04
## Lab.goalBoth:Race.ethnicity.Hispanic1     -3.642e-01  5.045e-01  2.083e+04
## Lab.goalSkills:Race.ethnicity.Hispanic1  2.959e-01  5.841e-01  2.082e+04
## Lab.goalBoth:Race.ethnicity.Asian1        -5.918e-01  4.647e-01  2.089e+04
## Lab.goalSkills:Race.ethnicity.Asian1      -6.796e-01  5.497e-01  2.088e+04
## Lab.goalBoth:Race.ethnicity.White1         7.425e-02  4.389e-01  2.083e+04
## Lab.goalSkills:Race.ethnicity.White1       9.721e-02  5.251e-01  2.083e+04
## Lab.goalBoth:Race.ethnicity.Unknown1      -6.352e-02  5.404e-01  2.067e+04
## Lab.goalSkills:Race.ethnicity.Unknown1    -3.829e-01  6.449e-01  2.030e+04
##                                           t value Pr(>|t|)
## (Intercept)                                 8.201 4.09e-16 ***
## student.score.pre                         111.716  < 2e-16 ***
## Lab.levelBFY                                2.942  0.00344 **
## Lab.levelFY.Calc                            0.078  0.93780
## Lab.goalBoth                                1.205  0.22849
## Lab.goalSkills                              1.944  0.05195 .
## GenderOther                                -2.022  0.04317 *
## GenderUnknown                              -2.270  0.02324 *
## GenderWoman                                -5.708 1.16e-08 ***
## Race.ethnicity.Native1                     -1.698  0.08946 .
## Race.ethnicity.Other1                      -1.292  0.19640
```

```
## Race.ethnicity.Black1                        -0.433  0.66533
## Race.ethnicity.Hispanic1                     -0.340  0.73386
## Race.ethnicity.Asian1                         1.864  0.06231 .
## Race.ethnicity.White1                         0.035  0.97179
## Race.ethnicity.Unknown1                       0.090  0.92850
## MajorChem.LifeSci                            -8.645  < 2e-16 ***
## MajorEngineering                             -4.879 1.07e-06 ***
## MajorMath.CS                                 -7.387 1.56e-13 ***
## MajorNonSci                                 -10.461  < 2e-16 ***
## MajorOtherSci                                -6.294 3.17e-10 ***
## MajorUndeclared                              -1.975  0.04830 *
## MajorUnknown                                 -2.198  0.02795 *
## Lab.goalBoth:GenderOther                      0.344  0.73121
## Lab.goalSkills:GenderOther                    0.895  0.37071
## Lab.goalBoth:GenderUnknown                    1.643  0.10032
## Lab.goalSkills:GenderUnknown                  0.336  0.73697
## Lab.goalBoth:GenderWoman                      3.989 6.66e-05 ***
## Lab.goalSkills:GenderWoman                    4.576 4.76e-06 ***
## Lab.goalBoth:Race.ethnicity.Native1           1.186  0.23562
## Lab.goalSkills:Race.ethnicity.Native1         2.244  0.02483 *
## Lab.goalBoth:Race.ethnicity.Other1            0.146  0.88378
## Lab.goalSkills:Race.ethnicity.Other1          0.516  0.60602
## Lab.goalBoth:Race.ethnicity.Black1           -1.404  0.16040
## Lab.goalSkills:Race.ethnicity.Black1          0.217  0.82826
## Lab.goalBoth:Race.ethnicity.Hispanic1        -0.722  0.47042
## Lab.goalSkills:Race.ethnicity.Hispanic1       0.507  0.61248
## Lab.goalBoth:Race.ethnicity.Asian1           -1.274  0.20280
## Lab.goalSkills:Race.ethnicity.Asian1         -1.236  0.21637
## Lab.goalBoth:Race.ethnicity.White1            0.169  0.86566
## Lab.goalSkills:Race.ethnicity.White1          0.185  0.85313
## Lab.goalBoth:Race.ethnicity.Unknown1         -0.118  0.90644
## Lab.goalSkills:Race.ethnicity.Unknown1       -0.594  0.55271
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 43 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
r2(mod1)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | ResponseId student.score.post ~ student.score.pre + Lab.goal + Lab.level + Major + Gend
##
##    Marginal R2: 0.412
## Conditional R2: 0.447
```

```r
r2(mod2)
```

```
##
## R-Squared for (Generalized) Linear (Mixed) Model
##
## Family : gaussian (identity)
## Formula: ~1 | ResponseId student.score.post ~ student.score.pre + Lab.level + Lab.goal * (Gender + Ra
##
##    Marginal R2: 0.413
## Conditional R2: 0.448
```

```r
noStandard.cols <- c('Lab.goal', '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:
## student.score.post.z ~ student.score.pre.z + Lab.goal + Lab.level +
##     Major + Gender + Race.ethnicity.Native + Race.ethnicity.Other +
##     Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##     Race.ethnicity.White + Race.ethnicity.Unknown + (1 | ResponseId)
##    Data: data
##
## REML criterion at convergence: 47557.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.3975 -0.5194  0.1195  0.6565  4.0090
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  ResponseId (Intercept) 0.03544  0.1883
##  Residual               0.55300  0.7436
## Number of obs: 20949, groups:  ResponseId, 380
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              1.970e-02  4.915e-02  5.396e+02   0.401 0.688743
## student.score.pre.z      6.056e-01  5.421e-03  2.093e+04 111.705  < 2e-16
## Lab.goalBoth             1.201e-01  3.660e-02  2.339e+02   3.281 0.001192
## Lab.goalSkills           2.153e-01  4.134e-02  2.528e+02   5.206 3.99e-07
## Lab.levelBFY             1.103e-01  3.908e-02  4.348e+02   2.822 0.004985
## Lab.levelFY.Calc         9.763e-04  3.338e-02  2.621e+02   0.029 0.976690
## MajorChem.LifeSci       -1.976e-01  2.284e-02  1.595e+04  -8.651  < 2e-16
## MajorEngineering        -9.780e-02  1.998e-02  1.798e+04  -4.894 9.97e-07
## MajorMath.CS            -1.646e-01  2.239e-02  1.988e+04  -7.352 2.03e-13
## MajorNonSci             -2.875e-01  2.775e-02  1.930e+04 -10.361  < 2e-16
## MajorOtherSci           -1.592e-01  2.553e-02  1.754e+04  -6.235 4.62e-10
## MajorUndeclared         -7.906e-02  3.970e-02  2.083e+04  -1.992 0.046422
## MajorUnknown            -1.866e-01  8.454e-02  2.090e+04  -2.208 0.027280
```

```
## GenderOther              -1.797e-01  4.916e-02  2.087e+04  -3.655 0.000258
## GenderUnknown            -8.080e-02  3.695e-02  2.092e+04  -2.187 0.028775
## GenderWoman              -4.130e-02  1.151e-02  2.092e+04  -3.589 0.000332
## Race.ethnicity.Native1   -3.139e-02  4.243e-02  2.076e+04  -0.740 0.459451
## Race.ethnicity.Other1    -9.857e-02  3.883e-02  2.077e+04  -2.539 0.011137
## Race.ethnicity.Black1    -7.827e-02  3.047e-02  1.942e+04  -2.569 0.010215
## Race.ethnicity.Hispanic1 -3.393e-02  2.520e-02  2.089e+04  -1.346 0.178286
## Race.ethnicity.Asian1     3.064e-02  2.259e-02  2.091e+04   1.357 0.174940
## Race.ethnicity.White1     1.024e-02  2.170e-02  2.084e+04   0.472 0.637185
## Race.ethnicity.Unknown1  -1.199e-02  2.683e-02  2.066e+04  -0.447 0.655071
##
## (Intercept)
## student.score.pre.z      ***
## Lab.goalBoth             **
## Lab.goalSkills           ***
## Lab.levelBFY             **
## Lab.levelFY.Calc
## MajorChem.LifeSci        ***
## MajorEngineering         ***
## MajorMath.CS             ***
## MajorNonSci              ***
## MajorOtherSci            ***
## MajorUndeclared          *
## MajorUnknown             *
## GenderOther              ***
## GenderUnknown            *
## GenderWoman              ***
## Race.ethnicity.Native1
## Race.ethnicity.Other1    *
## Race.ethnicity.Black1    *
## Race.ethnicity.Hispanic1
## Race.ethnicity.Asian1
## Race.ethnicity.White1
## Race.ethnicity.Unknown1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 23 > 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:
## student.score.post.z ~ student.score.pre.z + Lab.level + Lab.goal *
##     (Gender + Race.ethnicity.Native + Race.ethnicity.Other +
##         Race.ethnicity.Black + Race.ethnicity.Hispanic + Race.ethnicity.Asian +
##         Race.ethnicity.White + Race.ethnicity.Unknown) + Major +
##     (1 | ResponseId)
##    Data: data
```

```
##
## REML criterion at convergence: 47586
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.3701 -0.5208  0.1210  0.6548  4.0204
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  ResponseId (Intercept) 0.0352   0.1876
##  Residual               0.5524   0.7432
## Number of obs: 20949, groups:  ResponseId, 380
##
## Fixed effects:
##                                           Estimate Std. Error        df
## (Intercept)                              5.181e-02  6.837e-02  1.924e+03
## student.score.pre.z                      6.058e-01  5.422e-03  2.091e+04
## Lab.levelBFY                             1.149e-01  3.907e-02  4.356e+02
## Lab.levelFY.Calc                         2.606e-03  3.336e-02  2.620e+02
## Lab.goalBoth                             8.387e-02  6.963e-02  2.824e+03
## Lab.goalSkills                           1.591e-01  8.184e-02  3.435e+03
## GenderOther                             -2.477e-01  1.225e-01  2.076e+04
## GenderUnknown                           -1.817e-01  8.006e-02  2.089e+04
## GenderWoman                             -1.465e-01  2.566e-02  2.089e+04
## Race.ethnicity.Native1                  -1.933e-01  1.138e-01  2.077e+04
## Race.ethnicity.Other1                   -1.209e-01  9.361e-02  2.071e+04
## Race.ethnicity.Black1                   -2.607e-02  6.026e-02  1.532e+04
## Race.ethnicity.Hispanic1                -1.960e-02  5.764e-02  2.079e+04
## Race.ethnicity.Asian1                    1.010e-01  5.418e-02  2.089e+04
## Race.ethnicity.White1                    1.799e-03  5.088e-02  2.084e+04
## Race.ethnicity.Unknown1                  5.606e-03  6.248e-02  2.062e+04
## MajorChem.LifeSci                       -1.974e-01  2.283e-02  1.590e+04
## MajorEngineering                        -9.749e-02  1.998e-02  1.797e+04
## MajorMath.CS                            -1.654e-01  2.238e-02  1.986e+04
## MajorNonSci                             -2.903e-01  2.775e-02  1.927e+04
## MajorOtherSci                           -1.606e-01  2.552e-02  1.749e+04
## MajorUndeclared                         -7.837e-02  3.968e-02  2.081e+04
## MajorUnknown                            -1.858e-01  8.453e-02  2.088e+04
## Lab.goalBoth:GenderOther                 4.763e-02  1.387e-01  2.078e+04
## Lab.goalSkills:GenderOther               1.391e-01  1.554e-01  2.082e+04
## Lab.goalBoth:GenderUnknown               1.527e-01  9.291e-02  2.089e+04
## Lab.goalSkills:GenderUnknown             3.815e-02  1.136e-01  2.091e+04
## Lab.goalBoth:GenderWoman                 1.182e-01  2.964e-02  2.085e+04
## Lab.goalSkills:GenderWoman               1.573e-01  3.438e-02  2.064e+04
## Lab.goalBoth:Race.ethnicity.Native1      1.480e-01  1.248e-01  2.076e+04
## Lab.goalSkills:Race.ethnicity.Native1    3.418e-01  1.523e-01  2.079e+04
## Lab.goalBoth:Race.ethnicity.Other1       1.552e-02  1.062e-01  2.072e+04
## Lab.goalSkills:Race.ethnicity.Other1     6.420e-02  1.245e-01  2.072e+04
## Lab.goalBoth:Race.ethnicity.Black1      -1.028e-01  7.323e-02  1.798e+04
## Lab.goalSkills:Race.ethnicity.Black1     2.090e-02  9.636e-02  1.999e+04
## Lab.goalBoth:Race.ethnicity.Hispanic1   -4.817e-02  6.674e-02  2.083e+04
## Lab.goalSkills:Race.ethnicity.Hispanic1  3.914e-02  7.726e-02  2.082e+04
## Lab.goalBoth:Race.ethnicity.Asian1      -7.828e-02  6.146e-02  2.089e+04
## Lab.goalSkills:Race.ethnicity.Asian1    -8.989e-02  7.271e-02  2.088e+04
```

```
## Lab.goalBoth:Race.ethnicity.White1       9.821e-03  5.805e-02  2.083e+04
## Lab.goalSkills:Race.ethnicity.White1     1.286e-02  6.946e-02  2.083e+04
## Lab.goalBoth:Race.ethnicity.Unknown1    -8.401e-03  7.148e-02  2.067e+04
## Lab.goalSkills:Race.ethnicity.Unknown1  -5.064e-02  8.530e-02  2.030e+04
##                                         t value Pr(>|t|)
## (Intercept)                               0.758  0.44870
## student.score.pre.z                     111.716  < 2e-16 ***
## Lab.levelBFY                              2.942  0.00344 **
## Lab.levelFY.Calc                          0.078  0.93780
## Lab.goalBoth                              1.205  0.22849
## Lab.goalSkills                            1.944  0.05195 .
## GenderOther                              -2.022  0.04317 *
## GenderUnknown                            -2.270  0.02324 *
## GenderWoman                              -5.708 1.16e-08 ***
## Race.ethnicity.Native1                   -1.698  0.08946 .
## Race.ethnicity.Other1                    -1.292  0.19640
## Race.ethnicity.Black1                    -0.433  0.66533
## Race.ethnicity.Hispanic1                 -0.340  0.73386
## Race.ethnicity.Asian1                     1.864  0.06231 .
## Race.ethnicity.White1                     0.035  0.97179
## Race.ethnicity.Unknown1                   0.090  0.92850
## MajorChem.LifeSci                        -8.645  < 2e-16 ***
## MajorEngineering                         -4.879 1.07e-06 ***
## MajorMath.CS                             -7.387 1.56e-13 ***
## MajorNonSci                             -10.461  < 2e-16 ***
## MajorOtherSci                            -6.294 3.17e-10 ***
## MajorUndeclared                          -1.975  0.04830 *
## MajorUnknown                             -2.198  0.02795 *
## Lab.goalBoth:GenderOther                  0.344  0.73121
## Lab.goalSkills:GenderOther                0.895  0.37071
## Lab.goalBoth:GenderUnknown                1.643  0.10032
## Lab.goalSkills:GenderUnknown              0.336  0.73697
## Lab.goalBoth:GenderWoman                  3.989 6.66e-05 ***
## Lab.goalSkills:GenderWoman                4.576 4.76e-06 ***
## Lab.goalBoth:Race.ethnicity.Native1       1.186  0.23562
## Lab.goalSkills:Race.ethnicity.Native1     2.244  0.02483 *
## Lab.goalBoth:Race.ethnicity.Other1        0.146  0.88378
## Lab.goalSkills:Race.ethnicity.Other1      0.516  0.60602
## Lab.goalBoth:Race.ethnicity.Black1       -1.404  0.16040
## Lab.goalSkills:Race.ethnicity.Black1      0.217  0.82826
## Lab.goalBoth:Race.ethnicity.Hispanic1    -0.722  0.47042
## Lab.goalSkills:Race.ethnicity.Hispanic1   0.507  0.61248
## Lab.goalBoth:Race.ethnicity.Asian1       -1.274  0.20280
## Lab.goalSkills:Race.ethnicity.Asian1     -1.236  0.21637
## Lab.goalBoth:Race.ethnicity.White1        0.169  0.86566
## Lab.goalSkills:Race.ethnicity.White1      0.185  0.85313
## Lab.goalBoth:Race.ethnicity.Unknown1     -0.118  0.90644
## Lab.goalSkills:Race.ethnicity.Unknown1   -0.594  0.55271
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 43 > 12.
## Use print(x, correlation=TRUE)  or
```

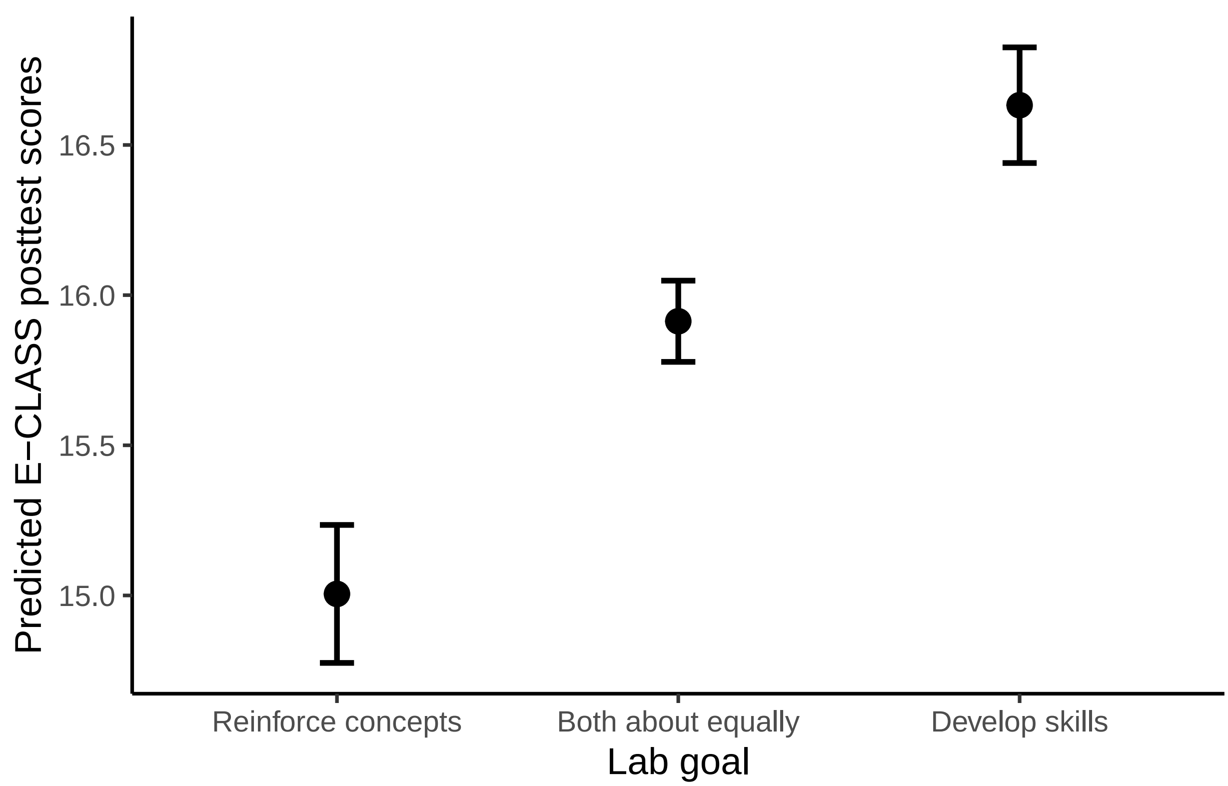
```
##     vcov(x)        if you need it
```

Marginal effects plots

```r
# Main effect of lab goal from Model 1
p1 <- plot_model(mod1, type = 'eff', terms = 'Lab.goal', dot.size = 4, line.size = 1,
                 ci.lvl = 0.67, title = '',
                 axis.title = 'Predicted E-CLASS 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"))
```

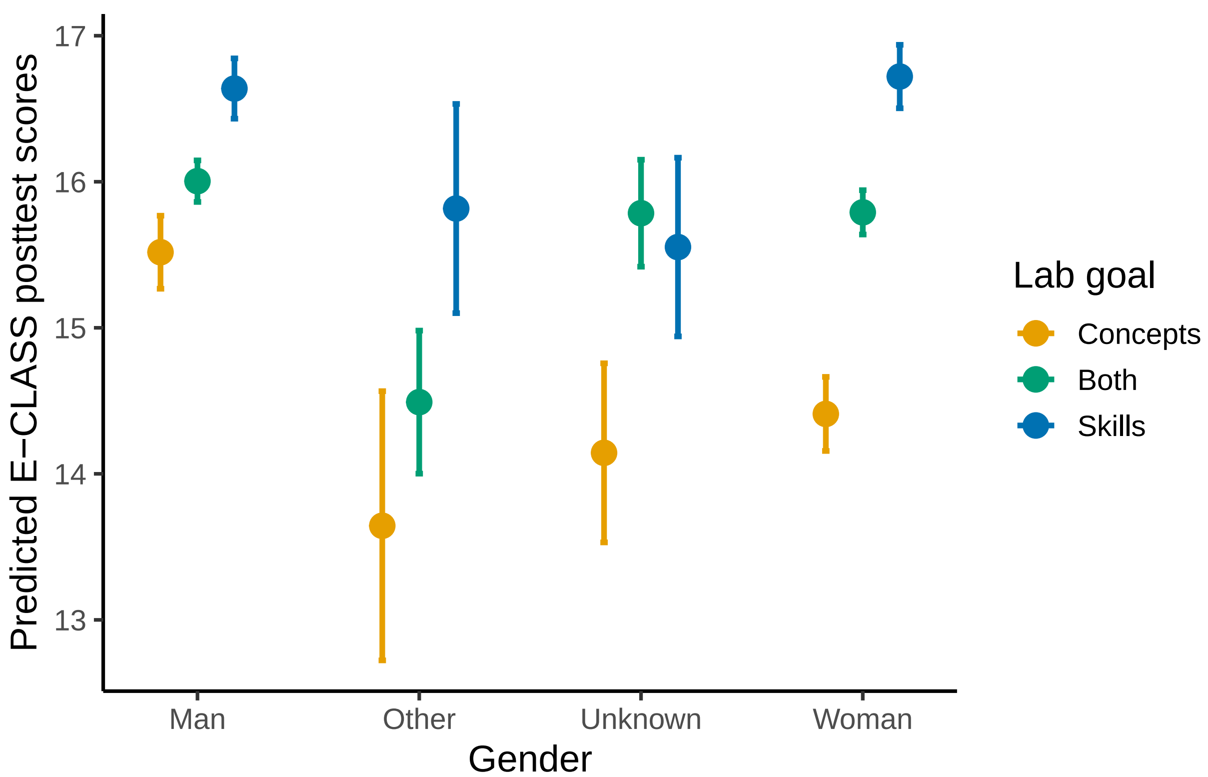
```
## Scale for 'x' is already present. Adding another scale for 'x', which
## will replace the existing scale.
```

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




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

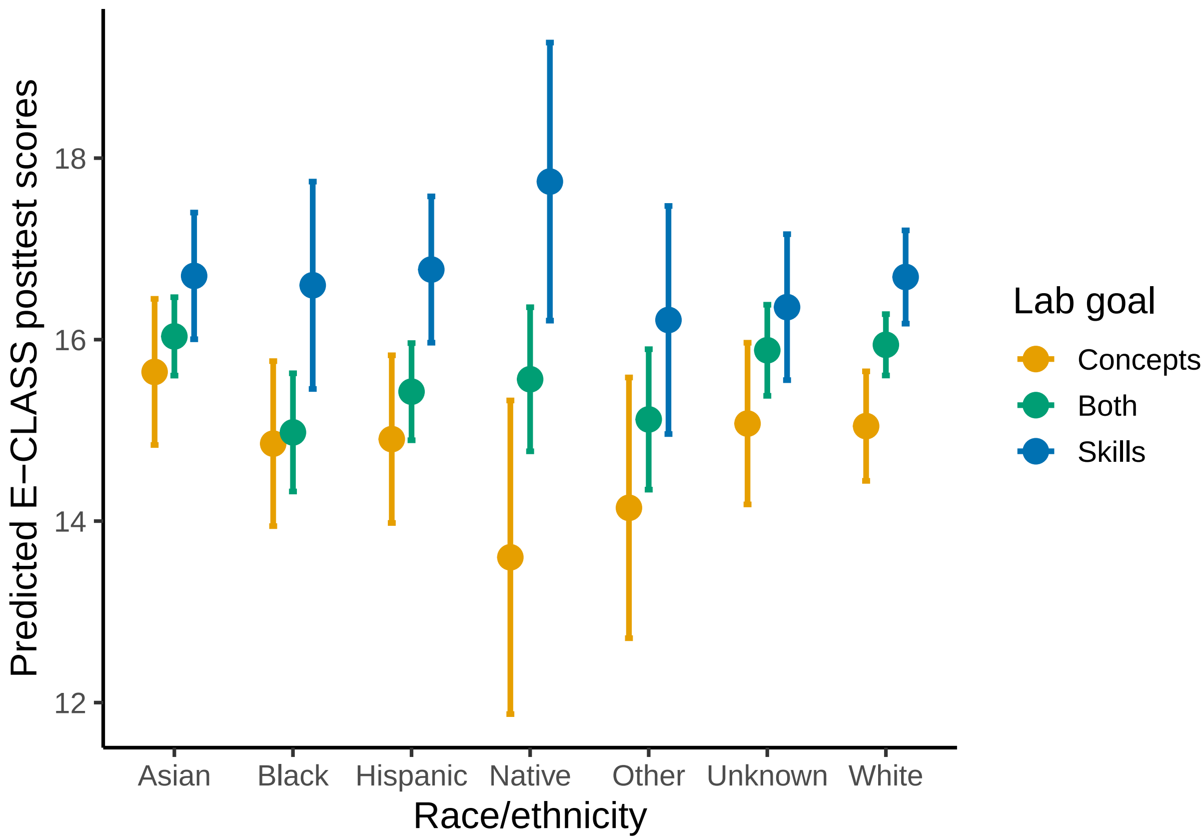
```r
p2 <- plot_model(mod2, type = 'eff', terms = c('Gender', 'Lab.goal'), dot.size = 4,
                 line.size = 1, ci.lvl = 0.67, title = '',
                 axis.title = 'Predicted E-CLASS posttest scores',
                 colors = c('#e69f00', '#009e74', '#0071b2'), dodge = 0.5) +
  theme(legend.position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

```r
p3.native <- plot_model(mod2, type = 'eff', terms = c('Race.ethnicity.Native [1]',
                                                      'Lab.goal'))
df.race.eff <- data.frame(p3.native$data) %>%
  mutate(race.ethnicity = 'Race.ethnicity.Native')
for(race in c(new.race.cols)){
  p3 <- plot_model(mod2, type = 'eff', terms = c(paste(race, ' [1]', sep = ''),
                                                 'Lab.goal'))
  df.race.eff <- rbind(df.race.eff, data.frame(p3$data) %>%
                         mutate(race.ethnicity = race))
}
```

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



Build measurement model for latent class variables

```r
df.matched[, names(df.matched) %like% "Q35|Q36"] <- data.frame(lapply(df.matched[, names(df.matched) %l

mod <- '
  agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q35_5 + Q36_6
  modeling =~ Q36_1 + Q36_2 + Q36_3 + Q36_4 + Q36_5
'
```

```r
fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q35|Q36"]))
```

```
## Warning in lav_model_vcov(lavmodel = lavmodel, lavsamplestats = lavsamplestats, : lavaan WARNING:
##     The variance-covariance matrix of the estimated parameters (vcov)
##     does not appear to be positive definite! The smallest eigenvalue
##     (= -1.151473e-17) is smaller than zero. This may be a symptom that
##     the model is not identified.
```

```r
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                         56
##
##   Number of observations                           180
##
##   Estimator                                       DWLS      Robust
##   Model Fit Test Statistic                     109.871     139.471
##   Degrees of freedom                                43          43
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  0.875
##   Shift parameter                                           13.924
##     for simple second-order correction (Mplus variant)
##
## Model test baseline model:
##
##   Minimum Function Test Statistic             5051.599    2455.822
##   Degrees of freedom                                55          55
##   P-value                                        0.000       0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.987       0.960
##   Tucker-Lewis Index (TLI)                       0.983       0.949
##
##   Robust Comparative Fit Index (CFI)                            NA
##   Robust Tucker-Lewis Index (TLI)                               NA
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.093       0.112
##   90 Percent Confidence Interval          0.072  0.115       0.092  0.133
##   P-value RMSEA <= 0.05                          0.001       0.000
##
##   Robust RMSEA                                                  NA
##   90 Percent Confidence Interval                                NA      NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.075       0.075
##
```

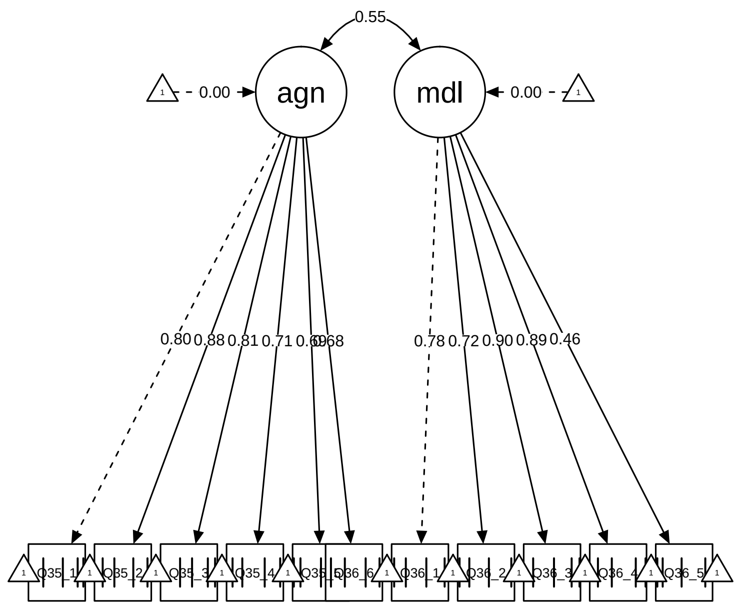
```
## Parameter Estimates:
##
##   Information                                 Expected
##   Information saturated (h1) model        Unstructured
##   Standard Errors                           Robust.sem
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q35_1             1.000                               0.796    0.796
##     Q35_2             1.107    0.061   18.092    0.000    0.881    0.881
##     Q35_3             1.014    0.056   18.121    0.000    0.807    0.807
##     Q35_4             0.889    0.060   14.795    0.000    0.707    0.707
##     Q35_5             0.864    0.069   12.490    0.000    0.687    0.687
##     Q36_6             0.852    0.071   12.088    0.000    0.678    0.678
##   modeling =~
##     Q36_1             1.000                               0.780    0.780
##     Q36_2             0.929    0.048   19.244    0.000    0.725    0.725
##     Q36_3             1.157    0.052   22.095    0.000    0.903    0.903
##     Q36_4             1.135    0.055   20.754    0.000    0.886    0.886
##     Q36_5             0.595    0.072    8.222    0.000    0.465    0.465
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~~
##     modeling          0.338    0.044    7.712    0.000    0.545    0.545
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.000                               0.000    0.000
##    .Q35_2             0.000                               0.000    0.000
##    .Q35_3             0.000                               0.000    0.000
##    .Q35_4             0.000                               0.000    0.000
##    .Q35_5             0.000                               0.000    0.000
##    .Q36_6             0.000                               0.000    0.000
##    .Q36_1             0.000                               0.000    0.000
##    .Q36_2             0.000                               0.000    0.000
##    .Q36_3             0.000                               0.000    0.000
##    .Q36_4             0.000                               0.000    0.000
##    .Q36_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
##     Q35_1|t1         -0.640    0.101   -6.336    0.000   -0.640   -0.640
##     Q35_1|t2          0.268    0.095    2.821    0.005    0.268    0.268
##     Q35_1|t3          1.111    0.118    9.411    0.000    1.111    1.111
##     Q35_1|t4          1.834    0.181   10.147    0.000    1.834    1.834
##     Q35_2|t1         -1.061    0.116   -9.176    0.000   -1.061   -1.061
##     Q35_2|t2         -0.385    0.096   -4.003    0.000   -0.385   -0.385
##     Q35_2|t3          0.477    0.098    4.885    0.000    0.477    0.477
##     Q35_2|t4          1.501    0.144   10.411    0.000    1.501    1.501
##     Q35_3|t1         -0.400    0.096   -4.151    0.000   -0.400   -0.400
```

```
##     Q35_3|t2          0.140    0.094    1.486    0.137    0.140    0.140
##     Q35_3|t3          0.967    0.111    8.677    0.000    0.967    0.967
##     Q35_3|t4          1.764    0.172   10.280    0.000    1.764    1.764
##     Q35_4|t1         -1.251    0.126   -9.939    0.000   -1.251   -1.251
##     Q35_4|t2         -0.589    0.100   -5.904    0.000   -0.589   -0.589
##     Q35_4|t3          0.446    0.097    4.592    0.000    0.446    0.446
##     Q35_4|t4          1.593    0.153   10.434    0.000    1.593    1.593
##     Q35_5|t1         -2.010    0.208   -9.656    0.000   -2.010   -2.010
##     Q35_5|t2         -1.085    0.117   -9.295    0.000   -1.085   -1.085
##     Q35_5|t3          0.000    0.094    0.000    1.000    0.000    0.000
##     Q35_5|t4          0.862    0.107    8.017    0.000    0.862    0.862
##     Q36_6|t1         -1.314    0.130  -10.116    0.000   -1.314   -1.314
##     Q36_6|t2         -0.415    0.097   -4.298    0.000   -0.415   -0.415
##     Q36_6|t3          0.540    0.099    5.469    0.000    0.540    0.540
##     Q36_6|t4          1.645    0.158   10.414    0.000    1.645    1.645
##     Q36_1|t1         -1.701    0.164  -10.365    0.000   -1.701   -1.701
##     Q36_1|t2         -0.674    0.102   -6.623    0.000   -0.674   -0.674
##     Q36_1|t3          0.282    0.095    2.969    0.003    0.282    0.282
##     Q36_1|t4          1.501    0.144   10.411    0.000    1.501    1.501
##     Q36_2|t1         -1.834    0.181  -10.147    0.000   -1.834   -1.834
##     Q36_2|t2         -0.822    0.106   -7.744    0.000   -0.822   -0.822
##     Q36_2|t3          0.126    0.094    1.338    0.181    0.126    0.126
##     Q36_2|t4          1.593    0.153   10.434    0.000    1.593    1.593
##     Q36_3|t1         -0.967    0.111   -8.677    0.000   -0.967   -0.967
##     Q36_3|t2          0.084    0.094    0.892    0.372    0.084    0.084
##     Q36_3|t3          1.013    0.113    8.931    0.000    1.013    1.013
##     Q36_3|t4          2.128    0.231    9.219    0.000    2.128    2.128
##     Q36_4|t1         -1.061    0.116   -9.176    0.000   -1.061   -1.061
##     Q36_4|t2         -0.282    0.095   -2.969    0.003   -0.282   -0.282
##     Q36_4|t3          0.882    0.108    8.152    0.000    0.882    0.882
##     Q36_4|t4          2.128    0.231    9.219    0.000    2.128    2.128
##     Q36_5|t1         -1.915    0.192   -9.948    0.000   -1.915   -1.915
##     Q36_5|t2         -1.164    0.121   -9.634    0.000   -1.164   -1.164
##     Q36_5|t3         -0.112    0.094   -1.189    0.234   -0.112   -0.112
##     Q36_5|t4          1.137    0.119    9.524    0.000    1.137    1.137
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.367                               0.367    0.367
##    .Q35_2             0.225                               0.225    0.225
##    .Q35_3             0.349                               0.349    0.349
##    .Q35_4             0.500                               0.500    0.500
##    .Q35_5             0.528                               0.528    0.528
##    .Q36_6             0.540                               0.540    0.540
##    .Q36_1             0.391                               0.391    0.391
##    .Q36_2             0.475                               0.475    0.475
##    .Q36_3             0.185                               0.185    0.185
##    .Q36_4             0.215                               0.215    0.215
##    .Q36_5             0.784                               0.784    0.784
##     agency            0.633    0.058   10.836    0.000    1.000    1.000
##     modeling          0.609    0.052   11.653    0.000    1.000    1.000
##
## Scales y*:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
```

```
##     Q35_1             1.000                                1.000    1.000
##     Q35_2             1.000                                1.000    1.000
##     Q35_3             1.000                                1.000    1.000
##     Q35_4             1.000                                1.000    1.000
##     Q35_5             1.000                                1.000    1.000
##     Q36_6             1.000                                1.000    1.000
##     Q36_1             1.000                                1.000    1.000
##     Q36_2             1.000                                1.000    1.000
##     Q36_3             1.000                                1.000    1.000
##     Q36_4             1.000                                1.000    1.000
##     Q36_5             1.000                                1.000    1.000
##
## Modification Indices:
##
##          lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 94    agency =~ Q36_1  0.090 -0.026  -0.020   -0.020   -0.020
## 95    agency =~ Q36_2  7.635 -0.237  -0.188   -0.188   -0.188
## 96    agency =~ Q36_3 12.783  0.302   0.240    0.240    0.240
## 97    agency =~ Q36_4  0.936 -0.082  -0.065   -0.065   -0.065
## 98    agency =~ Q36_5  0.136 -0.031  -0.025   -0.025   -0.025
## 99  modeling =~ Q35_1  0.748  0.072   0.056    0.056    0.056
## 100 modeling =~ Q35_2  6.165 -0.224  -0.175   -0.175   -0.175
## 101 modeling =~ Q35_3  0.003  0.005   0.004    0.004    0.004
## 102 modeling =~ Q35_4  0.109  0.028   0.022    0.022    0.022
## 103 modeling =~ Q35_5  1.563  0.109   0.085    0.085    0.085
## 104 modeling =~ Q36_6  0.128  0.030   0.024    0.024    0.024
## 105    Q35_1 ~~ Q35_2  1.368  0.068   0.068    0.235    0.235
## 106    Q35_1 ~~ Q35_3  0.062 -0.015  -0.015   -0.043   -0.043
## 107    Q35_1 ~~ Q35_4  1.266 -0.078  -0.078   -0.182   -0.182
## 108    Q35_1 ~~ Q35_5  3.056 -0.131  -0.131   -0.298   -0.298
## 109    Q35_1 ~~ Q36_6  0.061  0.016   0.016    0.037    0.037
## 110    Q35_1 ~~ Q36_1  0.890 -0.072  -0.072   -0.190   -0.190
## 111    Q35_1 ~~ Q36_2  0.827 -0.073  -0.073   -0.176   -0.176
## 112    Q35_1 ~~ Q36_3  4.314  0.123   0.123    0.472    0.472
## 113    Q35_1 ~~ Q36_4  0.887  0.060   0.060    0.215    0.215
## 114    Q35_1 ~~ Q36_5  1.680 -0.100  -0.100   -0.186   -0.186
## 115    Q35_2 ~~ Q35_3  1.847  0.080   0.080    0.286    0.286
## 116    Q35_2 ~~ Q35_4  0.020 -0.008  -0.008   -0.025   -0.025
## 117    Q35_2 ~~ Q35_5  0.966 -0.075  -0.075   -0.217   -0.217
## 118    Q35_2 ~~ Q36_6  0.105  0.022   0.022    0.063    0.063
## 119    Q35_2 ~~ Q36_1  0.008 -0.007  -0.007   -0.023   -0.023
## 120    Q35_2 ~~ Q36_2  3.449 -0.153  -0.153   -0.469   -0.469
## 121    Q35_2 ~~ Q36_3  1.100 -0.071  -0.071   -0.347   -0.347
## 122    Q35_2 ~~ Q36_4  2.361 -0.106  -0.106   -0.483   -0.483
## 123    Q35_2 ~~ Q36_5  0.016  0.010   0.010    0.025    0.025
## 124    Q35_3 ~~ Q35_4  1.678 -0.091  -0.091   -0.219   -0.219
## 125    Q35_3 ~~ Q35_5  0.492  0.051   0.051    0.119    0.119
## 126    Q35_3 ~~ Q36_6  1.389 -0.083  -0.083   -0.191   -0.191
## 127    Q35_3 ~~ Q36_1  0.753 -0.067  -0.067   -0.180   -0.180
## 128    Q35_3 ~~ Q36_2  1.875 -0.110  -0.110   -0.271   -0.271
## 129    Q35_3 ~~ Q36_3  2.582  0.102   0.102    0.402    0.402
## 130    Q35_3 ~~ Q36_4  0.003  0.004   0.004    0.013    0.013
## 131    Q35_3 ~~ Q36_5  0.045 -0.017  -0.017   -0.032   -0.032
## 132    Q35_4 ~~ Q35_5  2.486  0.108   0.108    0.210    0.210
```

```
## 133    Q35_4 ~~ Q36_6  0.974  0.065   0.065    0.124    0.124
## 134    Q35_4 ~~ Q36_1  0.135  0.029   0.029    0.067    0.067
## 135    Q35_4 ~~ Q36_2  0.684 -0.064  -0.064   -0.131   -0.131
## 136    Q35_4 ~~ Q36_3  1.228  0.076   0.076    0.249    0.249
## 137    Q35_4 ~~ Q36_4  0.010  0.007   0.007    0.021    0.021
## 138    Q35_4 ~~ Q36_5  0.678 -0.066  -0.066   -0.105   -0.105
## 139    Q35_5 ~~ Q36_6  0.882 -0.071  -0.071   -0.132   -0.132
## 140    Q35_5 ~~ Q36_1  0.322  0.042   0.042    0.092    0.092
## 141    Q35_5 ~~ Q36_2  0.021  0.010   0.010    0.020    0.020
## 142    Q35_5 ~~ Q36_3  0.749  0.065   0.065    0.208    0.208
## 143    Q35_5 ~~ Q36_4  0.115 -0.023  -0.023   -0.067   -0.067
## 144    Q35_5 ~~ Q36_5  4.070  0.147   0.147    0.229    0.229
## 145    Q36_6 ~~ Q36_1  0.343  0.045   0.045    0.097    0.097
## 146    Q36_6 ~~ Q36_2  1.100 -0.083  -0.083   -0.163   -0.163
## 147    Q36_6 ~~ Q36_3  4.001  0.125   0.125    0.395    0.395
## 148    Q36_6 ~~ Q36_4  1.117 -0.071  -0.071   -0.209   -0.209
## 149    Q36_6 ~~ Q36_5  0.423 -0.053  -0.053   -0.082   -0.082
## 150    Q36_1 ~~ Q36_2 26.559  0.284   0.284    0.658    0.658
## 151    Q36_1 ~~ Q36_3  9.857 -0.211  -0.211   -0.783   -0.783
## 152    Q36_1 ~~ Q36_4 10.823 -0.227  -0.227   -0.782   -0.782
## 153    Q36_1 ~~ Q36_5  7.138  0.165   0.165    0.298    0.298
## 154    Q36_2 ~~ Q36_3 22.015 -0.332  -0.332   -1.120   -1.120
## 155    Q36_2 ~~ Q36_4  0.127 -0.022  -0.022   -0.068   -0.068
## 156    Q36_2 ~~ Q36_5  9.108  0.180   0.180    0.295    0.295
## 157    Q36_3 ~~ Q36_4 20.595  0.283   0.283    1.420    1.420
## 158    Q36_3 ~~ Q36_5 11.589 -0.255  -0.255   -0.671   -0.671
## 159    Q36_4 ~~ Q36_5  4.586 -0.162  -0.162   -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% "Q35|Q36"] <- data.frame(lapply(df.matched[, names(df.matched) %li

fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q35|Q36"]))
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

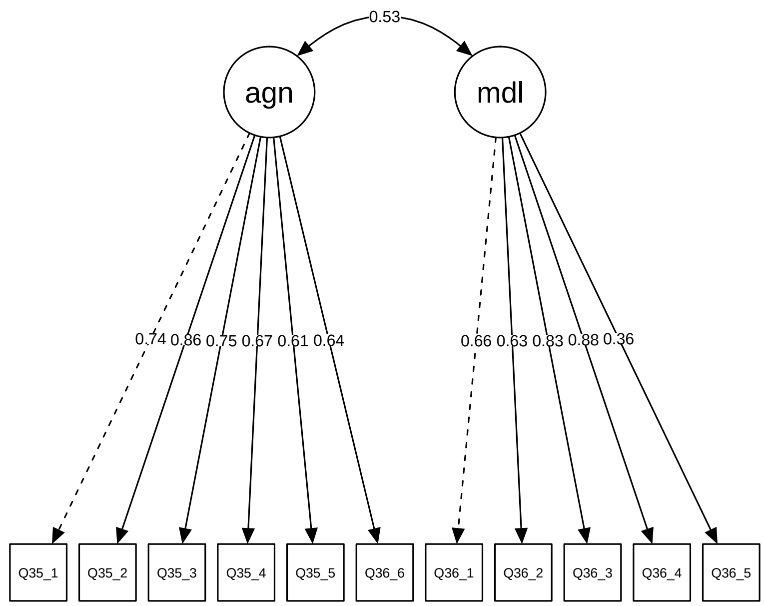
```
## lavaan 0.6-3 ended normally after 28 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         23
##
##   Number of observations                           180
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     172.938
##   Degrees of freedom                                43
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              974.856
##   Degrees of freedom                                55
```

```
##   P-value                                       0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                   0.859
##   Tucker-Lewis Index (TLI)                      0.819
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -2444.407
##   Loglikelihood unrestricted model (H1)     -2357.938
##
##   Number of free parameters                        23
##   Akaike (AIC)                               4934.814
##   Bayesian (BIC)                             5008.252
##   Sample-size adjusted Bayesian (BIC)        4935.410
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                         0.130
##   90 Percent Confidence Interval          0.110  0.150
##   P-value RMSEA <= 0.05                         0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                          0.071
##
## 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 =~
##     Q35_1             1.000                               0.786    0.738
##     Q35_2             1.249    0.113   11.100    0.000    0.981    0.865
##     Q35_3             1.132    0.116    9.764    0.000    0.889    0.754
##     Q35_4             0.886    0.103    8.602    0.000    0.696    0.667
##     Q35_5             0.782    0.099    7.886    0.000    0.614    0.613
##     Q36_6             0.844    0.102    8.299    0.000    0.663    0.644
##   modeling =~
##     Q36_1             1.000                               0.647    0.665
##     Q36_2             0.899    0.121    7.449    0.000    0.581    0.630
##     Q36_3             1.256    0.135    9.309    0.000    0.812    0.829
##     Q36_4             1.325    0.138    9.572    0.000    0.857    0.877
##     Q36_5             0.512    0.116    4.404    0.000    0.331    0.357
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency ~~
##     modeling          0.269    0.056    4.811    0.000    0.530    0.530
##
```

```
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.515    0.064    8.003    0.000    0.515    0.455
##    .Q35_2             0.324    0.056    5.828    0.000    0.324    0.252
##    .Q35_3             0.600    0.076    7.848    0.000    0.600    0.431
##    .Q35_4             0.605    0.071    8.507    0.000    0.605    0.555
##    .Q35_5             0.627    0.072    8.754    0.000    0.627    0.624
##    .Q36_6             0.620    0.072    8.622    0.000    0.620    0.585
##    .Q36_1             0.528    0.063    8.439    0.000    0.528    0.558
##    .Q36_2             0.513    0.060    8.622    0.000    0.513    0.603
##    .Q36_3             0.300    0.048    6.299    0.000    0.300    0.313
##    .Q36_4             0.220    0.045    4.902    0.000    0.220    0.230
##    .Q36_5             0.751    0.081    9.300    0.000    0.751    0.873
##     agency            0.617    0.112    5.522    0.000    1.000    1.000
##     modeling          0.418    0.088    4.776    0.000    1.000    1.000
##
## Modification Indices:
##
##         lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 26   agency =~ Q36_1  0.451  0.065   0.051    0.053    0.053
## 27   agency =~ Q36_2  2.126 -0.138  -0.108   -0.117   -0.117
## 28   agency =~ Q36_3  4.134  0.176   0.138    0.141    0.141
## 29   agency =~ Q36_4  2.625 -0.139  -0.109   -0.112   -0.112
## 30   agency =~ Q36_5  0.273  0.057   0.045    0.048    0.048
## 31 modeling =~ Q35_1  1.152  0.129   0.083    0.078    0.078
## 32 modeling =~ Q35_2  6.711 -0.296  -0.192   -0.169   -0.169
## 33 modeling =~ Q35_3  0.204  0.059   0.038    0.032    0.032
## 34 modeling =~ Q35_4  0.607  0.098   0.063    0.061    0.061
## 35 modeling =~ Q35_5  1.406  0.149   0.097    0.096    0.096
## 36 modeling =~ Q36_6  0.150  0.049   0.032    0.031    0.031
## 37    Q35_1 ~~ Q35_2  1.648  0.065   0.065    0.160    0.160
## 38    Q35_1 ~~ Q35_3  0.097  0.017   0.017    0.030    0.030
## 39    Q35_1 ~~ Q35_4  1.789 -0.067  -0.067   -0.119   -0.119
## 40    Q35_1 ~~ Q35_5  5.022 -0.111  -0.111   -0.195   -0.195
## 41    Q35_1 ~~ Q36_6  0.233  0.024   0.024    0.042    0.042
## 42    Q35_1 ~~ Q36_1  5.424 -0.102  -0.102   -0.196   -0.196
## 43    Q35_1 ~~ Q36_2  0.264 -0.022  -0.022   -0.043   -0.043
## 44    Q35_1 ~~ Q36_3  1.883  0.050   0.050    0.128    0.128
## 45    Q35_1 ~~ Q36_4  2.925  0.060   0.060    0.177    0.177
## 46    Q35_1 ~~ Q36_5  3.295 -0.091  -0.091   -0.147   -0.147
## 47    Q35_2 ~~ Q35_3  2.159  0.083   0.083    0.188    0.188
## 48    Q35_2 ~~ Q35_4  0.054 -0.012  -0.012   -0.026   -0.026
## 49    Q35_2 ~~ Q35_5  1.943 -0.067  -0.067   -0.149   -0.149
## 50    Q35_2 ~~ Q36_6  0.079  0.014   0.014    0.031    0.031
## 51    Q35_2 ~~ Q36_1  4.810  0.087   0.087    0.211    0.211
## 52    Q35_2 ~~ Q36_2  0.136 -0.014  -0.014   -0.035   -0.035
## 53    Q35_2 ~~ Q36_3  7.933 -0.094  -0.094   -0.301   -0.301
## 54    Q35_2 ~~ Q36_4  0.677 -0.026  -0.026   -0.098   -0.098
## 55    Q35_2 ~~ Q36_5  2.640  0.074   0.074    0.150    0.150
## 56    Q35_3 ~~ Q35_4  4.637 -0.117  -0.117   -0.195   -0.195
## 57    Q35_3 ~~ Q35_5  2.213  0.080   0.080    0.131    0.131
## 58    Q35_3 ~~ Q36_6  3.718 -0.105  -0.105   -0.172   -0.172
## 59    Q35_3 ~~ Q36_1  3.229 -0.086  -0.086   -0.153   -0.153
## 60    Q35_3 ~~ Q36_2  0.786 -0.041  -0.041   -0.075   -0.075
```

```
## 61    Q35_3 ~~ Q36_3  2.802  0.067   0.067    0.158    0.158
## 62    Q35_3 ~~ Q36_4  0.149  0.015   0.015    0.040    0.040
## 63    Q35_3 ~~ Q36_5  0.000  0.000   0.000    0.001    0.001
## 64    Q35_4 ~~ Q35_5  7.379  0.139   0.139    0.226    0.226
## 65    Q35_4 ~~ Q36_6  2.735  0.085   0.085    0.139    0.139
## 66    Q35_4 ~~ Q36_1  0.202  0.021   0.021    0.037    0.037
## 67    Q35_4 ~~ Q36_2  0.079 -0.013  -0.013   -0.023   -0.023
## 68    Q35_4 ~~ Q36_3  0.444  0.026   0.026    0.061    0.061
## 69    Q35_4 ~~ Q36_4  0.056  0.009   0.009    0.024    0.024
## 70    Q35_4 ~~ Q36_5  1.997 -0.075  -0.075   -0.111   -0.111
## 71    Q35_5 ~~ Q36_6  0.396 -0.032  -0.032   -0.052   -0.052
## 72    Q35_5 ~~ Q36_1  0.684  0.039   0.039    0.067    0.067
## 73    Q35_5 ~~ Q36_2  1.360  0.053   0.053    0.094    0.094
## 74    Q35_5 ~~ Q36_3  0.054  0.009   0.009    0.021    0.021
## 75    Q35_5 ~~ Q36_4  1.334 -0.043  -0.043   -0.115   -0.115
## 76    Q35_5 ~~ Q36_5  6.590  0.137   0.137    0.200    0.200
## 77    Q36_6 ~~ Q36_1  1.210  0.051   0.051    0.090    0.090
## 78    Q36_6 ~~ Q36_2  0.046 -0.010  -0.010   -0.017   -0.017
## 79    Q36_6 ~~ Q36_3  6.173  0.097   0.097    0.225    0.225
## 80    Q36_6 ~~ Q36_4  5.212 -0.084  -0.084   -0.229   -0.229
## 81    Q36_6 ~~ Q36_5  0.573 -0.040  -0.040   -0.059   -0.059
## 82    Q36_1 ~~ Q36_2 35.751  0.265   0.265    0.508    0.508
## 83    Q36_1 ~~ Q36_3  1.454 -0.054  -0.054   -0.136   -0.136
## 84    Q36_1 ~~ Q36_4 23.745 -0.226  -0.226   -0.662   -0.662
## 85    Q36_1 ~~ Q36_5 16.876  0.207   0.207    0.329    0.329
## 86    Q36_2 ~~ Q36_3 34.957 -0.249  -0.249   -0.634   -0.634
## 87    Q36_2 ~~ Q36_4  0.643  0.034   0.034    0.102    0.102
## 88    Q36_2 ~~ Q36_5 13.955  0.184   0.184    0.296    0.296
## 89    Q36_3 ~~ Q36_4 47.419  0.412   0.412    1.603    1.603
## 90    Q36_3 ~~ Q36_5  8.218 -0.125  -0.125   -0.264   -0.264
## 91    Q36_4 ~~ Q36_5  5.726 -0.102  -0.102   -0.251   -0.251
```

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



EFA

```
fa.parallel(unique(df.matched[, names(df.matched) %like% "Q35|Q36"]))
```

```
## 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.
```

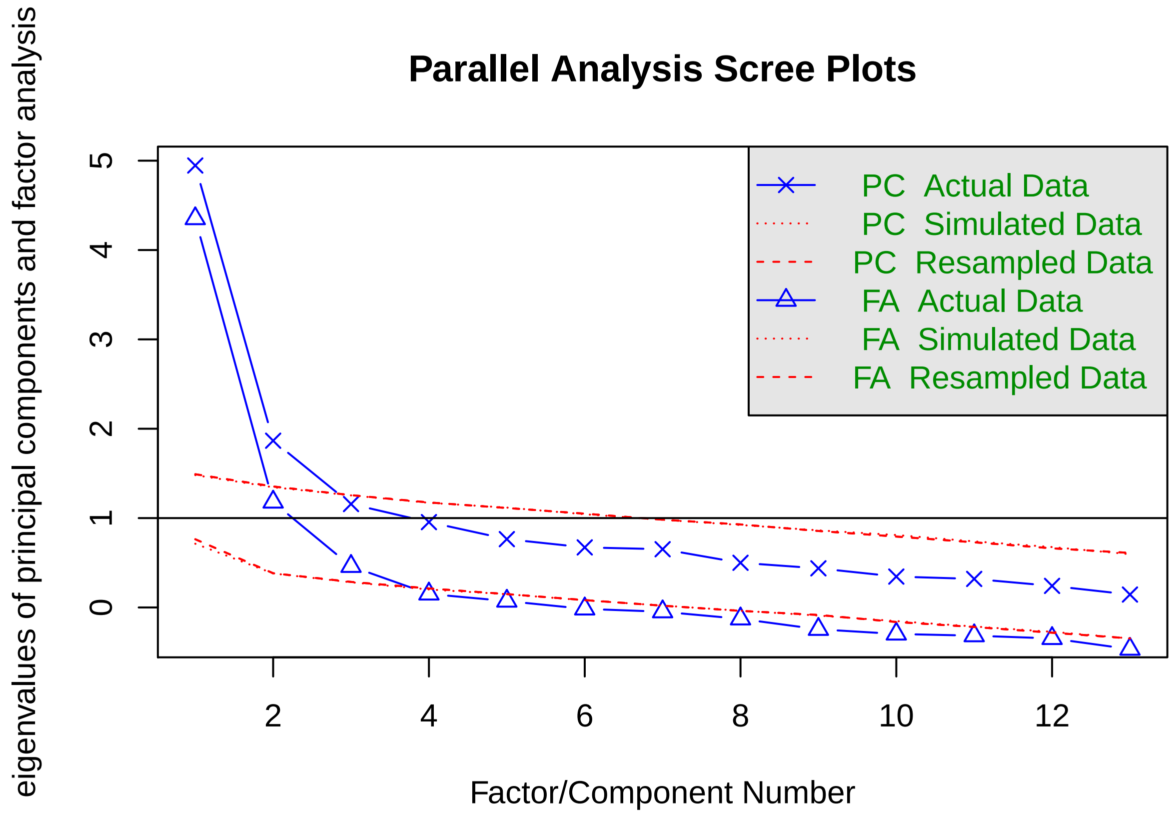
```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```
## 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 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 =  3  and the number of components =  2
```

```r
fit <- fa(unique(df.matched[, names(df.matched) %like% "Q35|Q36"]), 2)
```

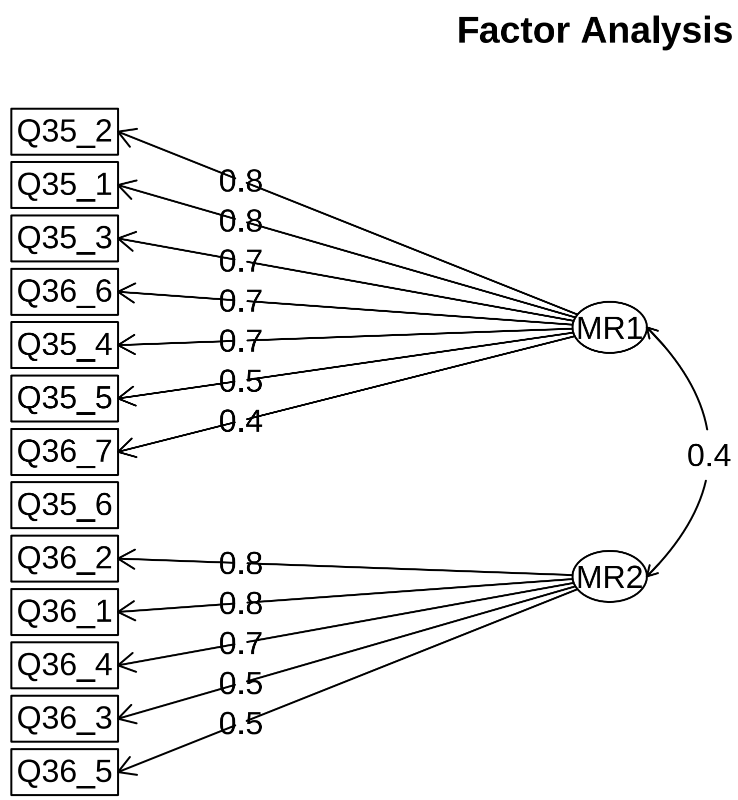
```
## Loading required namespace: GPArotation
```

```r
fit
```

```
## Factor Analysis using method =  minres
## Call: fa(r = unique(df.matched[, names(df.matched) %like% "Q35|Q36"]),
##     nfactors = 2)
## Standardized loadings (pattern matrix) based upon correlation matrix
##         MR1   MR2    h2   u2 com
## Q35_1  0.76 -0.02 0.570 0.43 1.0
## Q35_2  0.82 -0.02 0.664 0.34 1.0
## Q35_3  0.72  0.01 0.529 0.47 1.0
```

```
## Q35_4  0.66  0.03 0.451 0.55 1.0
## Q35_5  0.54  0.14 0.381 0.62 1.1
## Q35_6 -0.17  0.13 0.025 0.97 1.9
## Q36_1  0.01  0.79 0.626 0.37 1.0
## Q36_2 -0.12  0.83 0.618 0.38 1.0
## Q36_3  0.33  0.52 0.534 0.47 1.7
## Q36_4  0.17  0.67 0.578 0.42 1.1
## Q36_5 -0.04  0.49 0.226 0.77 1.0
## Q36_6  0.68  0.00 0.458 0.54 1.0
## Q36_7  0.45 -0.03 0.189 0.81 1.0
##
##                        MR1  MR2
## SS loadings           3.45 2.40
## Proportion Var        0.27 0.18
## Cumulative Var        0.27 0.45
## Proportion Explained  0.59 0.41
## Cumulative Proportion 0.59 1.00
##
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.45
## MR2 0.45 1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  78  and the objective function was  5.85 with Chi Squa
## The degrees of freedom for the model are 53  and the objective function was  1.22
##
## The root mean square of the residuals (RMSR) is  0.06
## The df corrected root mean square of the residuals is  0.08
##
## The harmonic number of observations is  180 with the empirical chi square  111.33  with prob <  5e-0
## The total number of observations was  180  with Likelihood Chi Square =  210.35  with prob <  1.3e-2
##
## Tucker Lewis Index of factoring reliability =  0.752
## RMSEA index =  0.132  and the 90 % confidence intervals are  0.111 0.147
## BIC =  -64.88
## Fit based upon off diagonal values = 0.97
## Measures of factor score adequacy
##                                                   MR1  MR2
## Correlation of (regression) scores with factors   0.94 0.92
## Multiple R square of scores with factors          0.88 0.85
## Minimum correlation of possible factor scores     0.76 0.70
```

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



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

```
mod <- '
  agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q36_6 + Q35_5
  modeling =~ Q36_1 + Q36_2 + Q36_4
'

fit <- sem(mod, unique(df.matched[, names(df.matched) %like% "Q35|Q36"]))
summary(fit, standardized = TRUE, fit.measures = TRUE, modindices = TRUE)
```

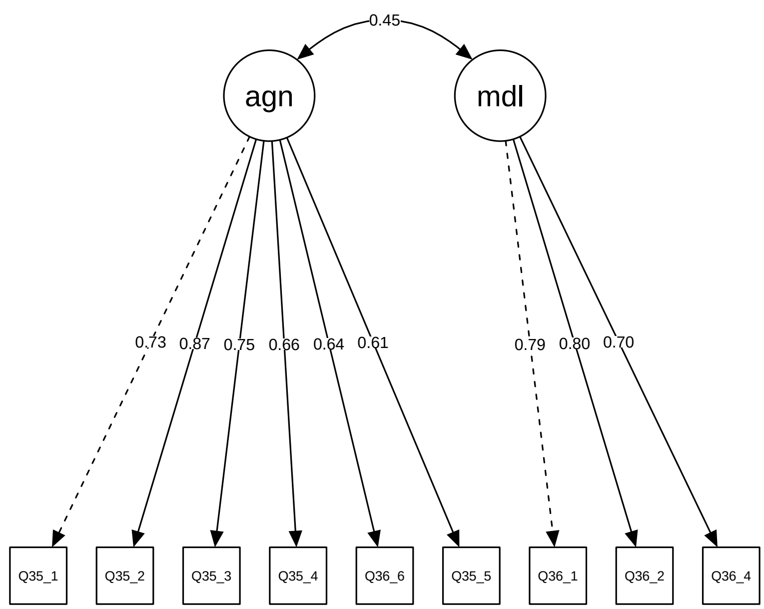
```
## lavaan 0.6-3 ended normally after 22 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         19
##
##   Number of observations                           180
##
##   Estimator                                         ML
##   Model Fit Test Statistic                      56.419
##   Degrees of freedom                                26
##   P-value (Chi-square)                           0.000
```

```
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              701.247
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.954
##   Tucker-Lewis Index (TLI)                       0.937
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -2029.286
##   Loglikelihood unrestricted model (H1)      -2001.076
##
##   Number of free parameters                         19
##   Akaike (AIC)                                4096.572
##   Bayesian (BIC)                              4157.238
##   Sample-size adjusted Bayesian (BIC)         4097.065
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.081
##   90 Percent Confidence Interval          0.052  0.109
##   P-value RMSEA <= 0.05                          0.042
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.057
##
## 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 =~
##     Q35_1             1.000                               0.780    0.733
##     Q35_2             1.273    0.115   11.081    0.000    0.993    0.875
##     Q35_3             1.133    0.118    9.637    0.000    0.884    0.749
##     Q35_4             0.889    0.104    8.526    0.000    0.693    0.664
##     Q36_6             0.848    0.103    8.241    0.000    0.661    0.643
##     Q35_5             0.784    0.100    7.817    0.000    0.612    0.610
##   modeling =~
##     Q36_1             1.000                               0.767    0.788
##     Q36_2             0.960    0.106    9.052    0.000    0.736    0.798
##     Q36_4             0.886    0.105    8.467    0.000    0.680    0.696
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
```

```
##   agency ~~
##     modeling          0.268    0.061    4.366    0.000    0.449    0.449
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             0.524    0.065    8.051    0.000    0.524    0.463
##    .Q35_2             0.302    0.055    5.493    0.000    0.302    0.235
##    .Q35_3             0.609    0.077    7.893    0.000    0.609    0.438
##    .Q35_4             0.608    0.071    8.522    0.000    0.608    0.558
##    .Q36_6             0.621    0.072    8.631    0.000    0.621    0.587
##    .Q35_5             0.630    0.072    8.768    0.000    0.630    0.627
##    .Q36_1             0.358    0.063    5.645    0.000    0.358    0.378
##    .Q36_2             0.309    0.057    5.416    0.000    0.309    0.363
##    .Q36_4             0.492    0.066    7.394    0.000    0.492    0.515
##     agency            0.608    0.111    5.466    0.000    1.000    1.000
##     modeling          0.588    0.105    5.578    0.000    1.000    1.000
##
## Modification Indices:
##
##         lhs op   rhs     mi    epc sepc.lv sepc.all sepc.nox
## 22   agency =~ Q36_1  0.885  0.090   0.070    0.072    0.072
## 23   agency =~ Q36_2 10.466 -0.296  -0.230   -0.250   -0.250
## 24   agency =~ Q36_4  6.863  0.251   0.196    0.201    0.201
## 25 modeling =~ Q35_1  0.009  0.010   0.007    0.007    0.007
## 26 modeling =~ Q35_2  1.529 -0.114  -0.087   -0.077   -0.077
## 27 modeling =~ Q35_3  0.194 -0.047  -0.036   -0.031   -0.031
## 28 modeling =~ Q35_4  0.515  0.074   0.057    0.055    0.055
## 29 modeling =~ Q36_6  0.153  0.041   0.031    0.030    0.030
## 30 modeling =~ Q35_5  2.257  0.156   0.119    0.119    0.119
## 31    Q35_1 ~~ Q35_2  1.421  0.062   0.062    0.155    0.155
## 32    Q35_1 ~~ Q35_3  0.344  0.032   0.032    0.056    0.056
## 33    Q35_1 ~~ Q35_4  1.328 -0.058  -0.058   -0.102   -0.102
## 34    Q35_1 ~~ Q36_6  0.373  0.031   0.031    0.054    0.054
## 35    Q35_1 ~~ Q35_5  4.231 -0.102  -0.102   -0.178   -0.178
## 36    Q35_1 ~~ Q36_1  4.904 -0.092  -0.092   -0.212   -0.212
## 37    Q35_1 ~~ Q36_2  0.026  0.006   0.006    0.016    0.016
## 38    Q35_1 ~~ Q36_4  6.736  0.116   0.116    0.228    0.228
## 39    Q35_2 ~~ Q35_3  1.746  0.076   0.076    0.178    0.178
## 40    Q35_2 ~~ Q35_4  0.271 -0.026  -0.026   -0.061   -0.061
## 41    Q35_2 ~~ Q36_6  0.000  0.001   0.001    0.001    0.001
## 42    Q35_2 ~~ Q35_5  2.882 -0.083  -0.083   -0.189   -0.189
## 43    Q35_2 ~~ Q36_1  3.294  0.067   0.067    0.205    0.205
## 44    Q35_2 ~~ Q36_2  3.361 -0.064  -0.064   -0.210   -0.210
## 45    Q35_2 ~~ Q36_4  1.488 -0.048  -0.048   -0.126   -0.126
## 46    Q35_3 ~~ Q35_4  3.868 -0.108  -0.108   -0.177   -0.177
## 47    Q35_3 ~~ Q36_6  3.164 -0.097  -0.097   -0.158   -0.158
## 48    Q35_3 ~~ Q35_5  2.588  0.087   0.087    0.141    0.141
## 49    Q35_3 ~~ Q36_1  2.142 -0.066  -0.066   -0.141   -0.141
## 50    Q35_3 ~~ Q36_2  0.104 -0.014  -0.014   -0.031   -0.031
## 51    Q35_3 ~~ Q36_4  2.890  0.082   0.082    0.150    0.150
## 52    Q35_4 ~~ Q36_6  2.916  0.088   0.088    0.144    0.144
## 53    Q35_4 ~~ Q35_5  7.711  0.143   0.143    0.231    0.231
## 54    Q35_4 ~~ Q36_1  0.289  0.023   0.023    0.050    0.050
## 55    Q35_4 ~~ Q36_2  0.314 -0.023  -0.023   -0.053   -0.053
```

```
## 56    Q35_4 ~~ Q36_4  0.677  0.039   0.039    0.071    0.071
## 57    Q36_6 ~~ Q35_5  0.319 -0.029  -0.029   -0.047   -0.047
## 58    Q36_6 ~~ Q36_1  2.050  0.063   0.063    0.133    0.133
## 59    Q36_6 ~~ Q36_2  0.191 -0.018  -0.018   -0.041   -0.041
## 60    Q36_6 ~~ Q36_4  0.598 -0.036  -0.036   -0.066   -0.066
## 61    Q35_5 ~~ Q36_1  0.281  0.023   0.023    0.049    0.049
## 62    Q35_5 ~~ Q36_2  1.043  0.042   0.042    0.095    0.095
## 63    Q35_5 ~~ Q36_4  0.071 -0.013  -0.013   -0.023   -0.023
## 64    Q36_1 ~~ Q36_2  6.863  0.290   0.290    0.872    0.872
## 65    Q36_1 ~~ Q36_4 10.465 -0.290  -0.290   -0.692   -0.692
## 66    Q36_2 ~~ Q36_4  0.885  0.082   0.082    0.210    0.210
```

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



This seems like a good model to move forward with. We drop two items from the modeling factor. For the record, I'm okay with adding them back in, but they will increase our variance maybe more than we can afford.

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

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

mod.sem <- '
  level: 1
    student.score.post ~ student.score.pre
  level: 2
    agency =~ Q35_1 + Q35_2 + Q35_3 + Q35_4 + Q36_6 + Q35_5
    modeling =~ Q36_1 + Q36_2 + Q36_4

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

    student.score.post ~ agency + modeling + Lab.goal.skills + Lab.goal.both
'

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

```
## lavaan 0.6-3 ended normally after 221 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                         39
##
##   Number of observations                         20949
##   Number of clusters [ResponseId]                  380
##
##   Estimator                                         ML
##   Model Fit Test Statistic                     291.436
##   Degrees of freedom                                48
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic            12054.008
##   Degrees of freedom                                66
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.980
##   Tucker-Lewis Index (TLI)                       0.972
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)            -139582.829
##   Loglikelihood unrestricted model (H1)    -139437.111
##
##   Number of free parameters                         39
##   Akaike (AIC)                              279243.659
##   Bayesian (BIC)                            279553.703
```

```
##   Sample-size adjusted Bayesian (BIC)      279429.762
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                        0.016
##   90 Percent Confidence Interval          0.014  0.017
##   P-value RMSEA <= 0.05                        1.000
##
## Standardized Root Mean Square Residual (corr metric):
##
##   SRMR (within covariance matrix)              0.000
##   SRMR (between covariance matrix)             0.096
##
## 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
##   student.score.post ~
##     student.scr.pr        0.720    0.007   97.351    0.000    0.720
##   Std.all
##
##     0.636
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .studnt.scr.pst    0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .studnt.scr.pst   31.890    0.315  101.399    0.000   31.890    0.596
##
##
## Level 2 [ResponseId]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   agency =~
##     Q35_1             1.000                               0.844    0.792
##     Q35_2             1.302    0.064   20.185    0.000    1.099    0.905
##     Q35_3             0.937    0.064   14.536    0.000    0.791    0.703
##     Q35_4             1.065    0.065   16.341    0.000    0.899    0.779
##     Q36_6             0.984    0.064   15.370    0.000    0.831    0.739
##     Q35_5             0.854    0.060   14.285    0.000    0.721    0.698
##   modeling =~
##     Q36_1             1.000                               0.591    0.662
##     Q36_2             1.367    0.150    9.102    0.000    0.807    0.892
##     Q36_4             1.121    0.104   10.733    0.000    0.662    0.645
```

```
##
## Regressions:
##                        Estimate  Std.Err  z-value  P(>|z|)   Std.lv
##   agency ~
##     Lab.goal.sklls        1.232    0.127    9.675    0.000    1.459
##     Lab.goal.both         0.231    0.112    2.074    0.038    0.274
##   modeling ~
##     Lab.goal.sklls        0.049    0.106    0.456    0.648    0.082
##     Lab.goal.both         0.271    0.097    2.782    0.005    0.458
##   student.score.post ~
##     agency                0.896    0.158    5.678    0.000    0.757
##     modeling             -0.006    0.187   -0.030    0.976   -0.003
##     Lab.goal.sklls        1.181    0.361    3.275    0.001    1.181
##     Lab.goal.both         1.252    0.284    4.416    0.000    1.252
##   Std.all
##
##     0.681
##     0.137
##
##     0.038
##     0.229
##
##     0.430
##    -0.002
##     0.313
##     0.355
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .Q35_1             1.620    0.105   15.441    0.000    1.620    1.521
##    .Q35_2             1.895    0.130   14.538    0.000    1.895    1.560
##    .Q35_3             1.645    0.104   15.868    0.000    1.645    1.461
##    .Q35_4             2.181    0.113   19.249    0.000    2.181    1.890
##    .Q36_6             2.079    0.107   19.399    0.000    2.079    1.850
##    .Q35_5             2.896    0.095   30.534    0.000    2.896    2.805
##    .Q36_1             2.998    0.092   32.539    0.000    2.998    3.360
##    .Q36_2             3.065    0.117   26.180    0.000    3.065    3.387
##    .Q36_4             2.615    0.104   25.092    0.000    2.615    2.549
##    .studnt.scr.pst    2.713    0.262   10.357    0.000    2.713    1.541
##    .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
##    .Q35_1             0.423    0.036   11.718    0.000    0.423    0.372
##    .Q35_2             0.268    0.033    8.020    0.000    0.268    0.181
##    .Q35_3             0.641    0.051   12.529    0.000    0.641    0.506
##    .Q35_4             0.523    0.045   11.564    0.000    0.523    0.393
##    .Q36_6             0.573    0.047   12.204    0.000    0.573    0.453
##    .Q35_5             0.547    0.044   12.535    0.000    0.547    0.513
##    .Q36_1             0.447    0.046    9.675    0.000    0.447    0.562
##    .Q36_2             0.168    0.062    2.696    0.007    0.168    0.205
##    .Q36_4             0.614    0.061   10.009    0.000    0.614    0.584
##    .studnt.scr.pst    2.199    0.282    7.789    0.000    2.199    0.710
```

```
##    .agency            0.467    0.053    8.842    0.000    0.655    0.655
##    .modeling          0.335    0.057    5.861    0.000    0.959    0.959
##
## Modification Indices:
##
##                    lhs op                rhs block group level     mi
## 3    student.score.pre ~~  student.score.pre     1     1     1  0.000
## 4   student.score.post ~1                        1     1     1  0.000
## 5    student.score.pre ~1                        1     1     1  0.000
## 35     Lab.goal.skills ~~    Lab.goal.skills     2     1     2  0.000
## 36     Lab.goal.skills ~~      Lab.goal.both     2     1     2  0.000
## 37       Lab.goal.both ~~      Lab.goal.both     2     1     2  0.000
## 48     Lab.goal.skills ~1                        2     1     2  0.000
## 49       Lab.goal.both ~1                        2     1     2  0.000
## 52   student.score.pre  ~ student.score.post     1     1     1  0.000
## 53              agency =~              Q36_1     2     1     2 32.465
## 54              agency =~              Q36_2     2     1     2  7.871
## 55              agency =~              Q36_4     2     1     2  2.605
## 56            modeling =~              Q35_1     2     1     2  0.424
## 57            modeling =~              Q35_2     2     1     2  2.128
## 58            modeling =~              Q35_3     2     1     2  5.530
## 59            modeling =~              Q35_4     2     1     2  0.751
## 60            modeling =~              Q36_6     2     1     2  2.543
## 61            modeling =~              Q35_5     2     1     2  0.927
## 62               Q35_1 ~~              Q35_2     2     1     2  6.474
## 63               Q35_1 ~~              Q35_3     2     1     2  0.127
## 64               Q35_1 ~~              Q35_4     2     1     2  2.440
## 65               Q35_1 ~~              Q36_6     2     1     2  0.971
## 66               Q35_1 ~~              Q35_5     2     1     2  4.153
## 67               Q35_1 ~~              Q36_1     2     1     2  7.988
## 68               Q35_1 ~~              Q36_2     2     1     2  0.917
## 69               Q35_1 ~~              Q36_4     2     1     2  7.956
## 70               Q35_1 ~~ student.score.post     2     1     2  3.972
## 71               Q35_2 ~~              Q35_3     2     1     2 17.747
## 72               Q35_2 ~~              Q35_4     2     1     2  8.683
## 73               Q35_2 ~~              Q36_6     2     1     2  0.379
## 74               Q35_2 ~~              Q35_5     2     1     2  3.801
## 75               Q35_2 ~~              Q36_1     2     1     2  8.873
## 76               Q35_2 ~~              Q36_2     2     1     2  2.512
## 77               Q35_2 ~~              Q36_4     2     1     2  3.316
## 78               Q35_2 ~~ student.score.post     2     1     2 10.657
## 79               Q35_3 ~~              Q35_4     2     1     2 15.360
## 80               Q35_3 ~~              Q36_6     2     1     2  9.561
## 81               Q35_3 ~~              Q35_5     2     1     2  2.453
## 82               Q35_3 ~~              Q36_1     2     1     2  4.102
## 83               Q35_3 ~~              Q36_2     2     1     2  0.102
## 84               Q35_3 ~~              Q36_4     2     1     2 26.766
## 85               Q35_3 ~~ student.score.post     2     1     2  4.778
## 86               Q35_4 ~~              Q36_6     2     1     2 22.221
## 87               Q35_4 ~~              Q35_5     2     1     2 16.764
## 88               Q35_4 ~~              Q36_1     2     1     2  8.375
## 89               Q35_4 ~~              Q36_2     2     1     2  2.650
## 90               Q35_4 ~~              Q36_4     2     1     2  0.068
## 91               Q35_4 ~~ student.score.post     2     1     2  9.521
```

```
## 92             Q36_6 ~~              Q35_5     2     1     2  0.473
## 93             Q36_6 ~~              Q36_1     2     1     2  1.643
## 94             Q36_6 ~~              Q36_2     2     1     2  4.371
## 95             Q36_6 ~~              Q36_4     2     1     2 12.548
## 96             Q36_6 ~~ student.score.post     2     1     2  0.013
## 97             Q35_5 ~~              Q36_1     2     1     2  3.005
## 98             Q35_5 ~~              Q36_2     2     1     2  1.288
## 99             Q35_5 ~~              Q36_4     2     1     2  6.694
## 100            Q35_5 ~~ student.score.post     2     1     2  1.875
## 101            Q36_1 ~~              Q36_2     2     1     2  6.773
## 102            Q36_1 ~~              Q36_4     2     1     2 20.407
## 103            Q36_1 ~~ student.score.post     2     1     2  0.018
## 104            Q36_2 ~~              Q36_4     2     1     2  9.761
## 105            Q36_2 ~~ student.score.post     2     1     2  0.905
## 106            Q36_4 ~~ student.score.post     2     1     2  1.952
## 107           agency ~~           modeling     2     1     2 13.249
## 108           agency  ~           modeling     2     1     2 13.255
## 109           agency  ~ student.score.post     2     1     2  9.570
## 110         modeling  ~             agency     2     1     2 13.270
## 111         modeling  ~ student.score.post     2     1     2 13.252
## 112     Lab.goal.skills  ~             agency     2     1     2  0.000
## 113     Lab.goal.skills  ~           modeling     2     1     2  0.000
## 114     Lab.goal.skills  ~ student.score.post     2     1     2  0.000
## 115     Lab.goal.skills  ~      Lab.goal.both     2     1     2  0.000
## 116       Lab.goal.both  ~             agency     2     1     2  0.000
## 117       Lab.goal.both  ~           modeling     2     1     2  0.000
## 118       Lab.goal.both  ~ student.score.post     2     1     2  0.000
## 119       Lab.goal.both  ~    Lab.goal.skills     2     1     2  0.000
##          epc sepc.lv sepc.all sepc.nox
## 3      0.000   0.000    0.000    0.000
## 4      0.000   0.000    0.000    0.000
## 5      0.000   0.000    0.000    0.000
## 35     0.000   0.000    0.000    0.000
## 36     0.000   0.000       NA    0.000
## 37     0.000   0.000    0.000    0.000
## 48     0.000   0.000    0.000    0.000
## 49     0.000   0.000    0.000    0.000
## 52     0.000   0.000    0.000    0.000
## 53     0.260   0.219    0.246    0.246
## 54    -0.123  -0.104   -0.115   -0.115
## 55     0.086   0.072    0.071    0.071
## 56     0.043   0.025    0.024    0.024
## 57    -0.090  -0.053   -0.044   -0.044
## 58     0.186   0.110    0.098    0.098
## 59     0.063   0.037    0.032    0.032
## 60     0.120   0.071    0.063    0.063
## 61     0.070   0.041    0.040    0.040
## 62     0.074   0.074    0.220    0.220
## 63     0.011   0.011    0.021    0.021
## 64    -0.047  -0.047   -0.099   -0.099
## 65    -0.030  -0.030   -0.060   -0.060
## 66    -0.059  -0.059   -0.122   -0.122
## 67    -0.072  -0.072   -0.166   -0.166
## 68     0.022   0.022    0.084    0.084
```

```
## 69    0.084   0.084    0.165    0.165
## 70    0.142   0.142    0.148    0.148
## 71    0.133   0.133    0.321    0.321
## 72   -0.093  -0.093   -0.248   -0.248
## 73   -0.019  -0.019   -0.049   -0.049
## 74   -0.057  -0.057   -0.148   -0.148
## 75    0.070   0.070    0.204    0.204
## 76   -0.034  -0.034   -0.162   -0.162
## 77   -0.050  -0.050   -0.124   -0.124
## 78   -0.225  -0.225   -0.293   -0.293
## 79   -0.135  -0.135   -0.233   -0.233
## 80   -0.109  -0.109   -0.179   -0.179
## 81    0.053   0.053    0.089    0.089
## 82   -0.062  -0.062   -0.115   -0.115
## 83   -0.009  -0.009   -0.027   -0.027
## 84    0.184   0.184    0.293    0.293
## 85   -0.185  -0.185   -0.156   -0.156
## 86    0.156   0.156    0.286    0.286
## 87    0.130   0.130    0.243    0.243
## 88    0.082   0.082    0.169    0.169
## 89   -0.042  -0.042   -0.142   -0.142
## 90    0.009   0.009    0.015    0.015
## 91    0.243   0.243    0.227    0.227
## 92   -0.022  -0.022   -0.040   -0.040
## 93    0.037   0.037    0.074    0.074
## 94    0.056   0.056    0.180    0.180
## 95   -0.120  -0.120   -0.203   -0.203
## 96    0.009   0.009    0.008    0.008
## 97    0.049   0.049    0.099    0.099
## 98    0.029   0.029    0.096    0.096
## 99   -0.085  -0.085   -0.146   -0.146
## 100   0.107   0.107    0.098    0.098
## 101  -0.400  -0.400   -1.462   -1.462
## 102   0.442   0.442    0.843    0.843
## 103   0.010   0.010    0.010    0.010
## 104  -0.520  -0.520   -1.621   -1.621
## 105   0.074   0.074    0.123    0.123
## 106  -0.118  -0.118   -0.102   -0.102
## 107   0.086   0.218    0.218    0.218
## 108   0.257   0.180    0.180    0.180
## 109 -39.033 -46.221  -81.357  -81.357
## 110   0.185   0.264    0.264    0.264
## 111   0.206   0.349    0.613    0.613
## 112   0.000   0.000    0.000    0.000
## 113   0.001   0.001    0.001    0.001
## 114   0.000   0.000    0.000    0.000
## 115   0.000   0.000    0.000    0.000
## 116   0.000   0.000    0.000    0.000
## 117   0.001   0.000    0.001    0.001
## 118   0.000   0.000    0.000    0.000
## 119   0.000   0.000    0.000    0.000
```