The Measurement Properties of Electoral Contestation

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Introduction

We begin with a descriptive question: What types of actions do Americans deem acceptable when someone disagrees with the results of an election? Here we focus on levels of support for various actions such as protesting, criticizing election integrity, burning the American flag, ballot recounts, or challenging the outcome in the courts. Moreover, we are interested in understanding the underlying structure of contestation preferences. Is a construct like contestation multidimensional?

On one hand, we might expect that contestation behaviors reside on a single underlying dimension, anchored by a preference for contestation behaviors on one pole, and an opposition to these behaviors at the other pole. However, there are several reasons to expect more nuance, due primarily to different norms surrounding such behaviors. For instance, while recounting ballots and supporting legal means to contest an election are common and generally perceived-to-be acceptable behaviors, attending a march or burning the flag are seen as more active and potentially transgressive behaviors. Contestation behaviors may be effectively disaggregated into forms that pose a relatively high cost for individual citizens (i.e, require action) versus forms of contestation that are passive and impose a low cost for citizens. They can also be viewed as a continuum of behaviors that range from less to more normatively acceptable.

Measuring Support for Contestation Behaviors

We measure support for behaviors aimed at contesting election results with a question battery that captures some of the most prominent ways election results are contested. Respondents were asked,

"Many people are unhappy with the outcomes of elections. How much do you support or oppose each of the following behaviors when people are unhappy with the outcome of an election?' '

- Attend a march or demonstration [, even if it might turn chaotic or dangerous]
- Publicly criticize the integrity or fairness of the election [on social media]
- Burn the American flag
- Support ballot recounts
- Contest the outcome in the courts

Respondents were asked to rate their support for each behavior on a 5-point scale, ranging from 1 (strongly support) to 5 (strongly oppose).

Recoding and Scaling

We rely on six data sets in this project. The **Western States Survey** conducted in both 2020 and 2024. The **Arizona Voter Project** election surveys, conducted in 2023 and 2024. And the 2022 Congressional

Election Study BYU module and the 2022 Congressional Election Study ASU module.

The `electoralContestation` package includes a number of helper functions to clean and recode these data. Downloading the package comes with the data electoral_contestation. Absent the CES modules, there are 9,403 observations.

```r
rm(list = ls())
#devtools::install_github("crweber9874/electoralContestation")
library(electoralContestation)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(lavaan)
```

```
## This is lavaan 0.6-19
## lavaan is FREE software! Please report any bugs.
```

```r
electoral_contestation <- electoral_contestation %>%
  filter(survey %in% c("wss20", "wss24", "avpw1", "avpw2"))

head(electoral_contestation)
```

```
## # A tibble: 6 x 29
##   black white asian american_indian latino   age married college faminc state
##   <dbl> <dbl> <dbl>           <dbl>  <dbl> <dbl>   <dbl>   <dbl>  <dbl> <chr>
## 1     0     1     0               0      0    61       1       1      0 4
## 2     0     1     0               0      0    41       1       1      1 4
## 3     0     0     0               1      0    25       0       1      0 4
## 4     0     1     0               0      0    76       0       1      0 4
## 5     0     1     0               0      0    63       0       0      0 4
## 6     0     1     0               0      0    72       1       0      1 4
## # i 19 more variables: year <dbl>, survey <chr>, caseidID <dbl>,
## #   caseidID22 <dbl>, attend_march <dbl>, burn_flag <dbl>, court <dbl>,
## #   recount <dbl>, criticize_election <dbl>, auth_1 <dbl>, auth_2 <dbl>,
## #   auth_3 <dbl>, auth_4 <dbl>, party3 <dbl>, christian <dbl>,
## #   post_experimental_condition <chr>, experimental_condition_post <chr>,
## #   experimental_condition_pre <chr>, pre_post_election <dbl>
```

```r
ordinal_data = c("burn_flag", "court", "recount", "criticize_election", "attend_march")

model <- ' f1 =~ court + recount + criticize_election +  attend_march
           court ~~ recount'

fit <- cfa(model, data = electoral_contestation,
           ordered = ordinal_data,
           )

# mod indices
summary(fit, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 20 iterations
##
##   Estimator                                         DWLS
##   Optimization method                             NLMINB
##   Number of model parameters                          21
##
##                                                     Used       Total
##   Number of observations                            9397        9403
##
## Model Test User Model:
##                                                 Standard      Scaled
##   Test Statistic                                   4.064       8.080
##   Degrees of freedom                                   1           1
##   P-value (Chi-square)                             0.044       0.004
##   Scaling correction factor                                    0.503
##   Shift parameter                                              0.000
##     simple second-order correction
##
## Model Test Baseline Model:
##
##   Test statistic                               10337.492    8732.950
##   Degrees of freedom                                   6           6
##   P-value                                          0.000       0.000
##   Scaling correction factor                                    1.184
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                      1.000       0.999
##   Tucker-Lewis Index (TLI)                         0.998       0.995
##
##   Robust Comparative Fit Index (CFI)                           0.999
```

```
##   Robust Tucker-Lewis Index (TLI)                            0.992
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.018       0.027
##   90 Percent confidence interval - lower         0.002       0.012
##   90 Percent confidence interval - upper         0.038       0.046
##   P-value H_0: RMSEA <= 0.050                    0.998       0.977
##   P-value H_0: RMSEA >= 0.080                    0.000       0.000
##
##   Robust RMSEA                                               0.030
##   90 Percent confidence interval - lower                     0.013
##   90 Percent confidence interval - upper                     0.050
##   P-value H_0: Robust RMSEA <= 0.050                         0.949
##   P-value H_0: Robust RMSEA >= 0.080                         0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.006       0.006
##
## Parameter Estimates:
##
##   Parameterization                               Delta
##   Standard errors                           Robust.sem
##   Information                                 Expected
##   Information saturated (h1) model        Unstructured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.782    0.020   39.380    0.000
##     criticize_lctn    1.322    0.038   34.689    0.000
##     attend_march      0.932    0.024   38.792    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.166    0.010   15.850    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -0.999    0.016  -64.161    0.000
```

```
##     court|t2         -0.437    0.013  -32.638    0.000
##     court|t3          0.395    0.013   29.679    0.000
##     court|t4          1.161    0.017   69.704    0.000
##     recount|t1       -1.637    0.022  -75.486    0.000
##     recount|t2       -1.135    0.016  -68.939    0.000
##     recount|t3       -0.307    0.013  -23.369    0.000
##     recount|t4        0.699    0.014   49.407    0.000
##     critcz_lctn|t1   -0.456    0.013  -33.942    0.000
##     critcz_lctn|t2    0.029    0.013    2.280    0.023
##     critcz_lctn|t3    0.692    0.014   48.994    0.000
##     critcz_lctn|t4    1.295    0.018   72.945    0.000
##     attend_mrch|t1   -1.048    0.016  -66.017    0.000
##     attend_mrch|t2   -0.545    0.014  -39.903    0.000
##     attend_mrch|t3    0.234    0.013   17.943    0.000
##     attend_mrch|t4    1.006    0.016   64.422    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.673
##    .recount           0.800
##    .criticize_lctn    0.428
##    .attend_march      0.716
##     f1                0.327    0.012   26.285    0.000
```

The fit is good. With just these items, I don't find much of a multidimensional structure. I actually don't find much evidence of a two factor model for the surveys other than the 2020 Western; there also seems to be a bit of a problem with the burning flag item, as it doesn't seem all that related to the other items.

```
electoral_contestation %>%
  select("burn_flag", "court", "criticize_election", "attend_march", "recount") %>%
  # deal with NA
  na.omit() %>%
  cor()
```

```
##                     burn_flag     court criticize_election attend_march
## burn_flag          1.00000000 0.1664893         0.03776088    0.2404490
## court              0.16648928 1.0000000         0.38231136    0.2582262
## criticize_election 0.03776088 0.3823114         1.00000000    0.3477097
## attend_march       0.24044899 0.2582262         0.34770971    1.0000000
## recount            0.12712382 0.3583892         0.27691073    0.2110060
##                      recount
## burn_flag          0.1271238
## court              0.3583892
## criticize_election 0.2769107
```

```
## attend_march       0.2110060
## recount            1.0000000
```

Testing for measurement invariance across party categories.

```r
# Configural Invariance: This assumes total variation of parameters across groups
fit_configural <- cfa(model, data = electoral_contestation, ordered = ordinal_data, group = "party3")
```

```
## Warning: lavaan->lav_data_full():
##    group variable 'party3' contains missing values
```

```r
# Scalar Invariance: This assumes equal factor loadings and intercepts across groups
fit_scalar2 <- cfa(model, data = electoral_contestation, ordered = ordinal_data, group = "party3", grou
```

```
## Warning: lavaan->lav_data_full():
##    group variable 'party3' contains missing values
```

```r
# summary(fit_scalar, fit.measures = TRUE)

# Compare models
anova(fit_configural, fit_scalar2)
```

```
##
## Scaled Chi-Squared Difference Test (method = "satorra.2000")
##
## lavaan->lavTestLRT():
##    lavaan NOTE: The "Chisq" column contains standard test statistics, not the
##    robust test that should be reported per model. A robust difference test is
##    a function of two standard (not robust) statistics.
##                Df AIC BIC    Chisq Chisq diff Df diff Pr(>Chisq)
## fit_configural  3           22.695
## fit_scalar2    33         1993.588     1491.5      30  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There fairly substantial differences in comparing the fully variant model to the one that is equal across partisan groups. There seems to be measurement variance. Here is the fully varying model – though note that without some common items it's not really possible to compare estimates

```r
summary(fit_configural, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 57 iterations
##
##   Estimator                                         DWLS
##   Optimization method                             NLMINB
```

```
##   Number of model parameters                        63
##
##   Number of observations per group:               Used       Total
##     3                                             3435        3439
##     1                                             4216        4217
##     2                                             1431        1432
##
## Model Test User Model:
##                                               Standard      Scaled
##   Test Statistic                                22.695      44.597
##   Degrees of freedom                                 3           3
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  0.509
##   Shift parameter                                            0.016
##     simple second-order correction
##   Test statistic for each group:
##     3                                            6.187       6.187
##     1                                           34.721      34.721
##     2                                            3.689       3.689
##
## Model Test Baseline Model:
##
##   Test statistic                             11572.116    9600.426
##   Degrees of freedom                                18          18
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.206
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.998       0.996
##   Tucker-Lewis Index (TLI)                       0.990       0.974
##
##   Robust Comparative Fit Index (CFI)                         0.993
##   Robust Tucker-Lewis Index (TLI)                            0.957
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.047       0.068
##   90 Percent confidence interval - lower         0.030       0.051
##   90 Percent confidence interval - upper         0.065       0.086
##   P-value H_0: RMSEA <= 0.050                    0.584       0.041
##   P-value H_0: RMSEA >= 0.080                    0.001       0.139
##
```

```
##   Robust RMSEA                                                 0.071
##   90 Percent confidence interval - lower                       0.053
##   90 Percent confidence interval - upper                       0.091
##   P-value H_0: Robust RMSEA <= 0.050                           0.031
##   P-value H_0: Robust RMSEA >= 0.080                           0.245
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                         0.014       0.014
##
## Parameter Estimates:
##
##   Parameterization                               Delta
##   Standard errors                           Robust.sem
##   Information                                 Expected
##   Information saturated (h1) model        Unstructured
##
##
## Group 1 [3]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.760    0.026   29.191    0.000
##     criticize_lctn    1.204    0.036   33.835    0.000
##     attend_march      0.979    0.028   35.292    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.154    0.015   10.202    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -1.134    0.027  -41.663    0.000
##     court|t2         -0.605    0.023  -26.462    0.000
##     court|t3          0.191    0.022    8.849    0.000
##     court|t4          0.983    0.026   38.402    0.000
##     recount|t1       -1.755    0.039  -45.082    0.000
##     recount|t2       -1.318    0.030  -44.351    0.000
##     recount|t3       -0.536    0.023  -23.767    0.000
##     recount|t4        0.456    0.022   20.546    0.000
```

```
##     critcz_lctn|t1   -0.367    0.022  -16.731    0.000
##     critcz_lctn|t2   -0.079    0.021   -3.702    0.000
##     critcz_lctn|t3    0.462    0.022   20.782    0.000
##     critcz_lctn|t4    1.129    0.027   41.560    0.000
##     attend_mrch|t1   -0.782    0.024  -32.653    0.000
##     attend_mrch|t2   -0.265    0.022  -12.218    0.000
##     attend_mrch|t3    0.478    0.022   21.454    0.000
##     attend_mrch|t4    1.258    0.029   43.630    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.566
##    .recount           0.749
##    .criticize_lctn    0.370
##    .attend_march      0.584
##     f1                0.434    0.018   24.165    0.000
##
##
## Group 2 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.830    0.036   22.900    0.000
##     criticize_lctn    1.125    0.060   18.830    0.000
##     attend_march      0.987    0.050   19.657    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.104    0.018    5.793    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -0.857    0.022  -38.754    0.000
##     court|t2         -0.245    0.020  -12.553    0.000
##     court|t3          0.524    0.020   25.824    0.000
##     court|t4          1.314    0.027   49.087    0.000
##     recount|t1       -1.571    0.031  -50.638    0.000
##     recount|t2       -1.018    0.023  -43.460    0.000
##     recount|t3       -0.243    0.020  -12.430    0.000
##     recount|t4        0.867    0.022   39.090    0.000
```

```
##     critcz_lctn|t1   -0.511    0.020  -25.250    0.000
##     critcz_lctn|t2    0.153    0.019    7.881    0.000
##     critcz_lctn|t3    0.844    0.022   38.332    0.000
##     critcz_lctn|t4    1.447    0.029   50.268    0.000
##     attend_mrch|t1   -1.311    0.027  -49.053    0.000
##     attend_mrch|t2   -0.777    0.022  -35.992    0.000
##     attend_mrch|t3   -0.054    0.019   -2.772    0.006
##     attend_mrch|t4    0.793    0.022   36.567    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.692
##    .recount           0.788
##    .criticize_lctn    0.611
##    .attend_march      0.700
##     f1                0.308    0.022   14.216    0.000
##
##
## Group 3 [2]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.861    0.051   16.741    0.000
##     criticize_lctn    1.373    0.091   15.110    0.000
##     attend_march      1.092    0.064   17.057    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.144    0.024    5.990    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -1.100    0.042  -26.474    0.000
##     court|t2         -0.564    0.035  -16.047    0.000
##     court|t3          0.450    0.034   13.088    0.000
##     court|t4          1.153    0.043   27.116    0.000
##     recount|t1       -1.590    0.054  -29.499    0.000
##     recount|t2       -1.113    0.042  -26.638    0.000
##     recount|t3       -0.143    0.033   -4.307    0.000
##     recount|t4        0.788    0.037   21.213    0.000
```

```
##     critcz_lctn|t1   -0.483    0.035  -13.974    0.000
##     critcz_lctn|t2   -0.013    0.033   -0.396    0.692
##     critcz_lctn|t3    0.781    0.037   21.065    0.000
##     critcz_lctn|t4    1.294    0.045   28.452    0.000
##     attend_mrch|t1   -1.060    0.041  -25.927    0.000
##     attend_mrch|t2   -0.576    0.035  -16.356    0.000
##     attend_mrch|t3    0.440    0.034   12.827    0.000
##     attend_mrch|t4    1.100    0.042   26.474    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.703
##    .recount           0.780
##    .criticize_lctn    0.440
##    .attend_march      0.646
##     f1                0.297    0.028   10.490    0.000
```

```
electoral_contestation$survey <- as.character(electoral_contestation$survey)
# one hot encode survey
electoral_contestation <- electoral_contestation %>%
  mutate(wss20 = as.numeric(survey == "wss20"),
         wss24 = as.numeric(survey == "wss24"),
         avpw1 = as.numeric(survey == "avpw1"),
         avpw2 = as.numeric(survey == "avpw2"))



model <- ' f1 =~ court + recount + criticize_election +  attend_march + burn_flag
           court ~~ recount
           f1 ~ wss20 + wss24 + avpw1'

fit_modified <- sem(model, data = electoral_contestation,
           ordered = ordinal_data,
           group = "party3"
           )
```

```
## Warning: lavaan->lav_data_full():
##    group variable 'party3' contains missing values
```

```
summary(fit_modified, fit.measures = TRUE)
```

```
## lavaan 0.6-19 ended normally after 68 iterations
##
##   Estimator                                       DWLS
##   Optimization method                           NLMINB
```

```
##   Number of model parameters                        87
##
##   Number of observations per group:               Used       Total
##     3                                             3435        3439
##     1                                             4216        4217
##     2                                             1430        1432
##
## Model Test User Model:
##                                               Standard      Scaled
##   Test Statistic                               650.290     672.427
##   Degrees of freedom                                48          48
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  0.989
##   Shift parameter                                           14.758
##     simple second-order correction
##   Test statistic for each group:
##     3                                          421.406     421.406
##     1                                          163.405     163.405
##     2                                           87.616      87.616
##
## Model Test Baseline Model:
##
##   Test statistic                             12675.889   10259.234
##   Degrees of freedom                                30          30
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.236
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.952       0.939
##   Tucker-Lewis Index (TLI)                       0.970       0.962
##
##   Robust Comparative Fit Index (CFI)                            NA
##   Robust Tucker-Lewis Index (TLI)                               NA
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.064       0.066
##   90 Percent confidence interval - lower         0.060       0.061
##   90 Percent confidence interval - upper         0.069       0.070
##   P-value H_0: RMSEA <= 0.050                    0.000       0.000
##   P-value H_0: RMSEA >= 0.080                    0.000       0.000
##
```

```
##   Robust RMSEA                                                  NA
##   90 Percent confidence interval - lower                        NA
##   90 Percent confidence interval - upper                        NA
##   P-value H_0: Robust RMSEA <= 0.050                            NA
##   P-value H_0: Robust RMSEA >= 0.080                            NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                         0.030       0.030
##
## Parameter Estimates:
##
##   Parameterization                               Delta
##   Standard errors                           Robust.sem
##   Information                                 Expected
##   Information saturated (h1) model        Unstructured
##
##
## Group 1 [3]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.714    0.027   26.956    0.000
##     criticize_lctn    1.415    0.045   31.426    0.000
##     attend_march      0.941    0.028   33.992    0.000
##     burn_flag         0.627    0.034   18.447    0.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 ~
##     wss20            -1.031    0.048  -21.386    0.000
##     wss24            -0.352    0.043   -8.261    0.000
##     avpw1             0.055    0.051    1.084    0.278
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.195    0.014   13.713    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
```

```
##     court|t1         -1.503    0.054  -27.586    0.000
##     court|t2         -0.969    0.054  -18.101    0.000
##     court|t3         -0.147    0.054   -2.744    0.006
##     court|t4          0.678    0.055   12.305    0.000
##     recount|t1       -2.359    0.066  -35.800    0.000
##     recount|t2       -1.922    0.063  -30.482    0.000
##     recount|t3       -1.122    0.062  -18.170    0.000
##     recount|t4       -0.084    0.059   -1.424    0.154
##     critcz_lctn|t1   -1.260    0.059  -21.224    0.000
##     critcz_lctn|t2   -0.821    0.057  -14.322    0.000
##     critcz_lctn|t3   -0.103    0.057   -1.800    0.072
##     critcz_lctn|t4    0.674    0.059   11.496    0.000
##     attend_mrch|t1   -1.170    0.055  -21.218    0.000
##     attend_mrch|t2   -0.621    0.054  -11.572    0.000
##     attend_mrch|t3    0.167    0.054    3.119    0.002
##     attend_mrch|t4    0.979    0.056   17.391    0.000
##     burn_flag|t1     -0.587    0.131   -4.496    0.000
##     burn_flag|t2      0.369    0.126    2.921    0.003
##     burn_flag|t3      1.077    0.128    8.431    0.000
##     burn_flag|t4      1.738    0.131   13.292    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.638
##    .recount           0.815
##    .criticize_lctn    0.274
##    .attend_march      0.679
##    .burn_flag         0.857
##    .f1                0.362    0.016   23.239    0.000
##
##
## Group 2 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.840    0.034   24.999    0.000
##     criticize_lctn    1.074    0.045   23.957    0.000
##     attend_march      1.104    0.045   24.567    0.000
##     burn_flag         0.991    0.041   24.109    0.000
##
## Regressions:
```

```
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 ~
##     wss20             0.012    0.046    0.269    0.788
##     wss24            -0.157    0.046   -3.421    0.001
##     avpw1            -0.081    0.056   -1.451    0.147
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.121    0.015    8.011    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -0.984    0.068  -14.447    0.000
##     court|t2         -0.371    0.066   -5.618    0.000
##     court|t3          0.400    0.066    6.063    0.000
##     court|t4          1.190    0.070   17.027    0.000
##     recount|t1       -1.519    0.060  -25.228    0.000
##     recount|t2       -0.958    0.059  -16.170    0.000
##     recount|t3       -0.173    0.059   -2.942    0.003
##     recount|t4        0.946    0.061   15.615    0.000
##     critcz_lctn|t1   -0.739    0.088   -8.367    0.000
##     critcz_lctn|t2   -0.069    0.085   -0.816    0.415
##     critcz_lctn|t3    0.619    0.086    7.218    0.000
##     critcz_lctn|t4    1.219    0.090   13.598    0.000
##     attend_mrch|t1   -1.383    0.060  -22.992    0.000
##     attend_mrch|t2   -0.848    0.058  -14.578    0.000
##     attend_mrch|t3   -0.125    0.058   -2.154    0.031
##     attend_mrch|t4    0.722    0.059   12.226    0.000
##     burn_flag|t1     -0.631    0.079   -7.970    0.000
##     burn_flag|t2      0.006    0.076    0.076    0.940
##     burn_flag|t3      0.803    0.077   10.474    0.000
##     burn_flag|t4      1.412    0.079   17.921    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.704
##    .recount           0.792
##    .criticize_lctn    0.659
##    .attend_march      0.640
##    .burn_flag         0.710
##    .f1                0.296    0.018   16.781    0.000
##
```

```
##
## Group 3 [2]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 =~
##     court             1.000
##     recount           0.850    0.051   16.614    0.000
##     criticize_lctn    1.283    0.076   16.855    0.000
##     attend_march      1.139    0.065   17.570    0.000
##     burn_flag         0.777    0.058   13.492    0.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   f1 ~
##     wss20            -0.530    0.076   -6.937    0.000
##     wss24            -0.324    0.075   -4.314    0.000
##     avpw1            -0.233    0.088   -2.648    0.008
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .court ~~
##    .recount           0.140    0.023    6.210    0.000
##
## Thresholds:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     court|t1         -1.519    0.106  -14.290    0.000
##     court|t2         -0.979    0.103   -9.551    0.000
##     court|t3          0.046    0.103    0.443    0.658
##     court|t4          0.762    0.105    7.227    0.000
##     recount|t1       -2.015    0.102  -19.802    0.000
##     recount|t2       -1.542    0.098  -15.789    0.000
##     recount|t3       -0.568    0.098   -5.781    0.000
##     recount|t4        0.372    0.098    3.790    0.000
##     critcz_lctn|t1   -1.020    0.109   -9.372    0.000
##     critcz_lctn|t2   -0.497    0.105   -4.731    0.000
##     critcz_lctn|t3    0.355    0.105    3.382    0.001
##     critcz_lctn|t4    0.889    0.107    8.305    0.000
##     attend_mrch|t1   -1.456    0.103  -14.102    0.000
##     attend_mrch|t2   -0.967    0.101   -9.587    0.000
##     attend_mrch|t3    0.061    0.101    0.606    0.545
##     attend_mrch|t4    0.729    0.104    7.031    0.000
##     burn_flag|t1     -0.617    0.157   -3.921    0.000
```

```
##     burn_flag|t2      0.004    0.151    0.023    0.981
##     burn_flag|t3      0.981    0.152    6.456    0.000
##     burn_flag|t4      1.565    0.156   10.033    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .court             0.701
##    .recount           0.784
##    .criticize_lctn    0.507
##    .attend_march      0.611
##    .burn_flag         0.819
##    .f1                0.299    0.027   11.025    0.000
```