The Effect of Cooperation Intention on Metaethical Ratings

Jean Luo and Yi Zhang

2021-11-08

Contents

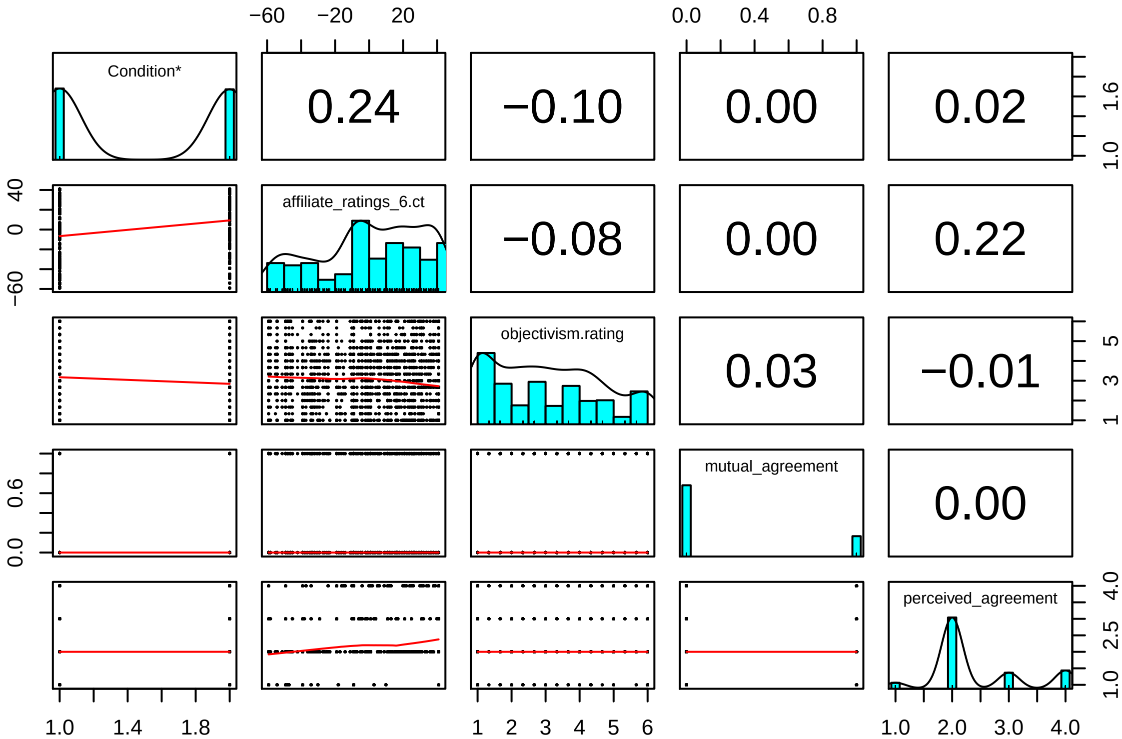
Load and examine data

```
## Warning: Missing column names filled in: 'X1' [1]

## Parsed with column specification:
## cols(
##   .default = col_double(),
##   Condition = col_character(),
##   gender = col_character(),
##   race = col_character()
## )

## See spec(...) for full column specifications.

## # A tibble: 6 x 25
##      X1    id Condition statement affiliate_ratin~ affiliate_ratin~
##   <dbl> <dbl> <chr>         <dbl>            <dbl>            <dbl>
## 1     1     1 COOPERAT~         1               61              100
## 2     2     1 COOPERAT~         2               61              100
## 3     3     1 COOPERAT~         3               61              100
## 4     4     1 COOPERAT~         4               61              100
## 5     5     1 COOPERAT~         5               61              100
## 6     6     1 COOPERAT~         6               61              100
## # ... with 19 more variables: affiliate_ratings_6 <dbl>,
## #   perceived_agreement <dbl>, reasonableness <dbl>, perceived_poli_1 <dbl>,
## #   perceived_poli_2 <dbl>, age <dbl>, gender <chr>, race <chr>,
## #   political_orien <dbl>, affiliate_ratings_1.ct <dbl>,
## #   affiliate_ratings_2.ct <dbl>, affiliate_ratings_6.ct <dbl>,
## #   reasonableness.ct <dbl>, fact.rating <dbl>, corr_ans.rating <dbl>,
## #   mistake.rating <dbl>, objectivism.rating <dbl>, consensus.ct <dbl>,
## #   mutual_agreement <dbl>
```



Testing model assumptions

```
#Baseline model
m0 <- lmer(objectivism.rating ~ (1|statement) + (1|id), data = data)
vc_m0 <- as.data.frame(VarCorr(m0))
# ICC/Deff (person; cluster size = 9)
icc_person <- vc_m0$vcov[1] / sum(vc_m0$vcov)
# ICC (item; cluster size = 367)
icc_item <- vc_m0$vcov[2] / sum(vc_m0$vcov)
# ICC (person + item)
c("ICC(person + item)" = sum(vc_m0$vcov[1:2]) / sum(vc_m0$vcov)) #.40
```

ICC

```
## ICC(person + item)
##           0.404038
```

```
#ICC andd design effect for person
c("ICC(person)" = icc_person,
  "Deff(person)" = (1 - icc_item) + (9 - 1) * icc_person)
```

```
##  ICC(person) Deff(person)
##    0.3140867    3.4227419
```

```r
#ICC and design effect for item
c("ICC(item)" = icc_item,
  "Deff(item)" = (1 - icc_person) + (367 - 1) * icc_item)
```

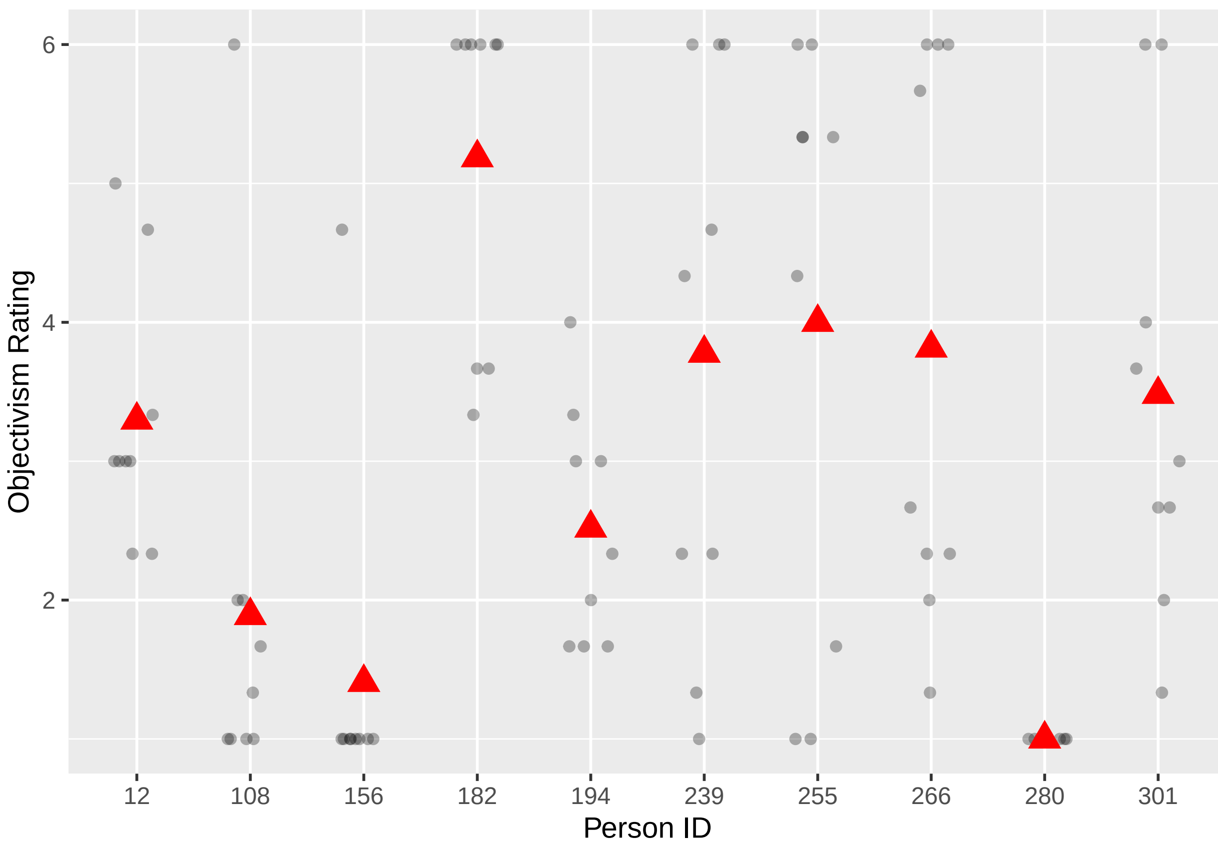
```
##   ICC(item)  Deff(item)
##  0.08995134 33.60810292
```

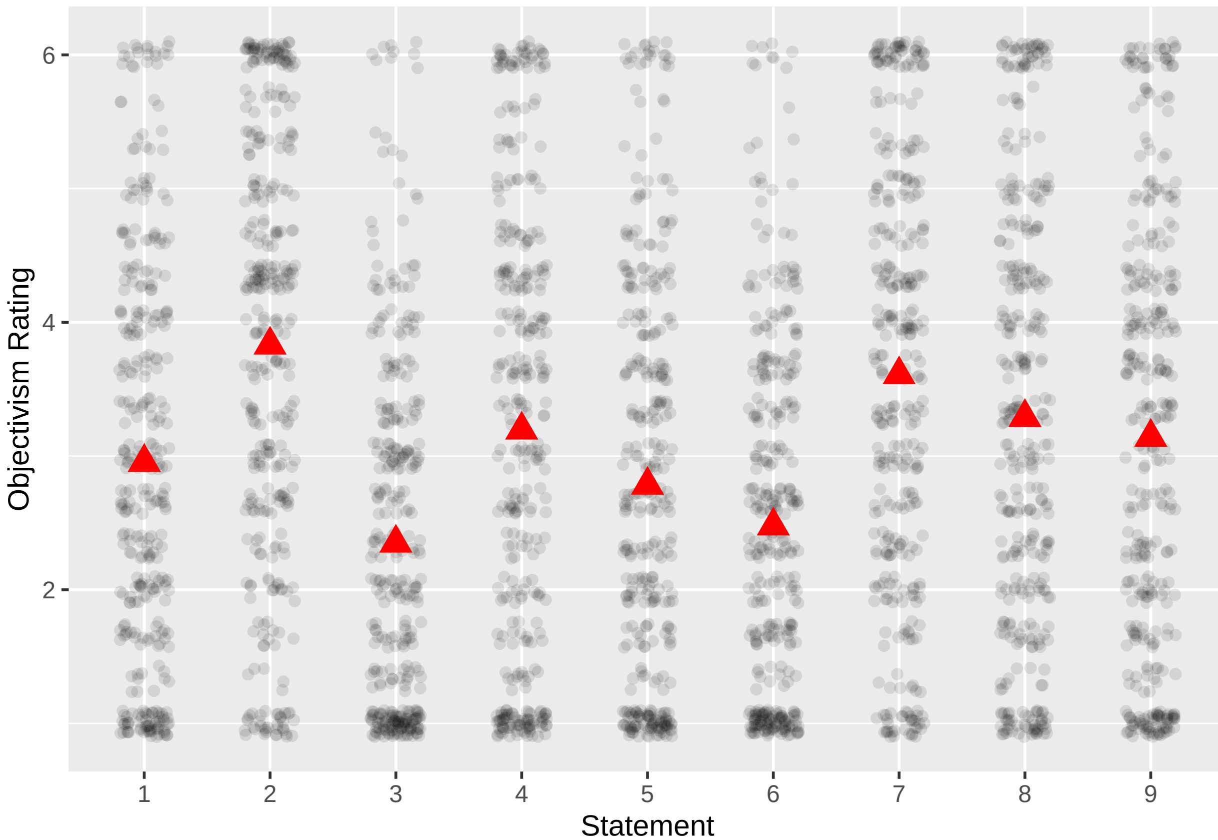
ICC for `person` is .31, which means that 31% of the variance in objectivity rating was at the between-person level. The corresponding design effect was 3.42.

ICC for `item` is .09, meaning that 9% of the variance in objectivity rating was at the between-item level. The corresponding design effect was 33.61.

Since both design effects are larger than 1.1, we include both the person and item levels in our multilevel model.

Visualizing the Data The figure below shows the variation in objectivism rating at both the person and item levels.





Model Equations Repeated-Measure level (Lv 1):

$$\text{objectivism}_{j,k} = \beta_{j,k} + e_{jk}$$

Between-cell (Person $\times$ Item) level (Lv 2):

$$\beta_{0(j,k)} = \gamma_{00} + \beta_{1j}Condition + \beta_{2k}perceived\_agreement + u_{0j} + v_{0k}$$

Person level (Lv 2a) random slopes

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

Item level (Lv2b) random slopes

$$\beta_{2k} = \gamma_{20} + v_{2k}$$

Baseline model First, we fit a random-intercept model using condition at the person-level and perceived agreement at the item-level to predict objectivism ratings.

```
# Fit a linear growth model with no random slopes
m1 <- lmer(objectivism.rating ~ Condition + perceived_agreement + (1|statement) + (1|id), data = data)
summary(m1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## objectivism.rating ~ Condition + perceived_agreement + (1 | statement) +
##     (1 | id)
```

```
##    Data: data
##
## REML criterion at convergence: 11083.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8679 -0.6522 -0.0717  0.6353  3.8244
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  id        (Intercept) 0.7961   0.8923
##  statement (Intercept) 0.2336   0.4833
##  Residual              1.5474   1.2440
## Number of obs: 3186, groups:  id, 354; statement, 9
##
## Fixed effects:
##                          Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)               3.25821    0.23389  33.35489  13.930 1.85e-15 ***
## ConditionCOOPERATE WITH  -0.31398    0.10460 351.00001  -3.002  0.00288 **
## perceived_agreement      -0.01341    0.06350 351.00001  -0.211  0.83288
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) CCOOPW
## CCOOPERATEW -0.211
## prcvd_grmnt -0.653 -0.017
```

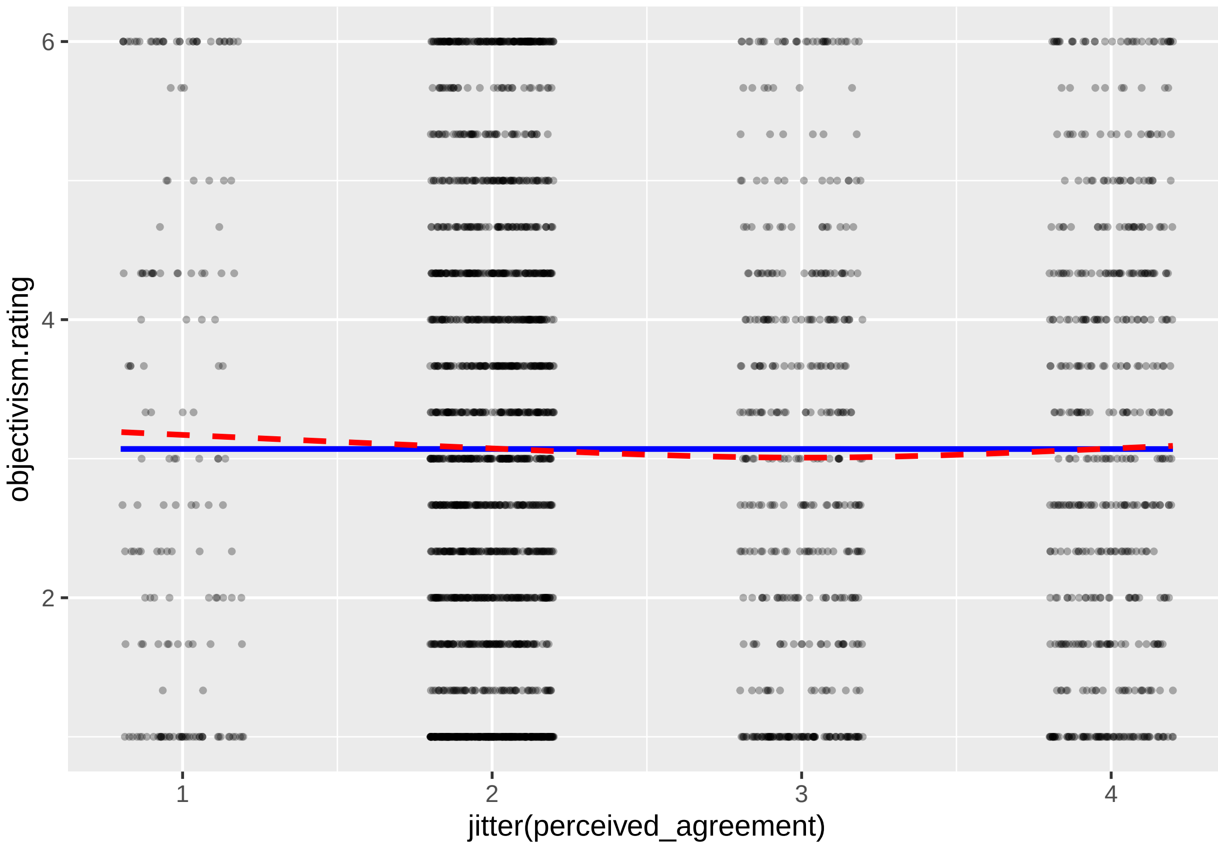
```
confint(m1, parm = "beta_")
```

```
##                              2.5 %     97.5 %
## (Intercept)               2.7998178  3.7166053
## ConditionCOOPERATE WITH -0.5189492 -0.1090207
## perceived_agreement     -0.1378398  0.1110200
```

```
augment(m1) %>%
  ggplot(aes(x = jitter(perceived_agreement), y = objectivism.rating)) +
  geom_point(size = 0.7, alpha = 0.3) +
  geom_smooth(col = "blue", se = FALSE) + # blue line from data
  geom_smooth(aes(y = .fitted),
    col = "red",
    se = FALSE, linetype = "dashed"
  )  # red line from model
```

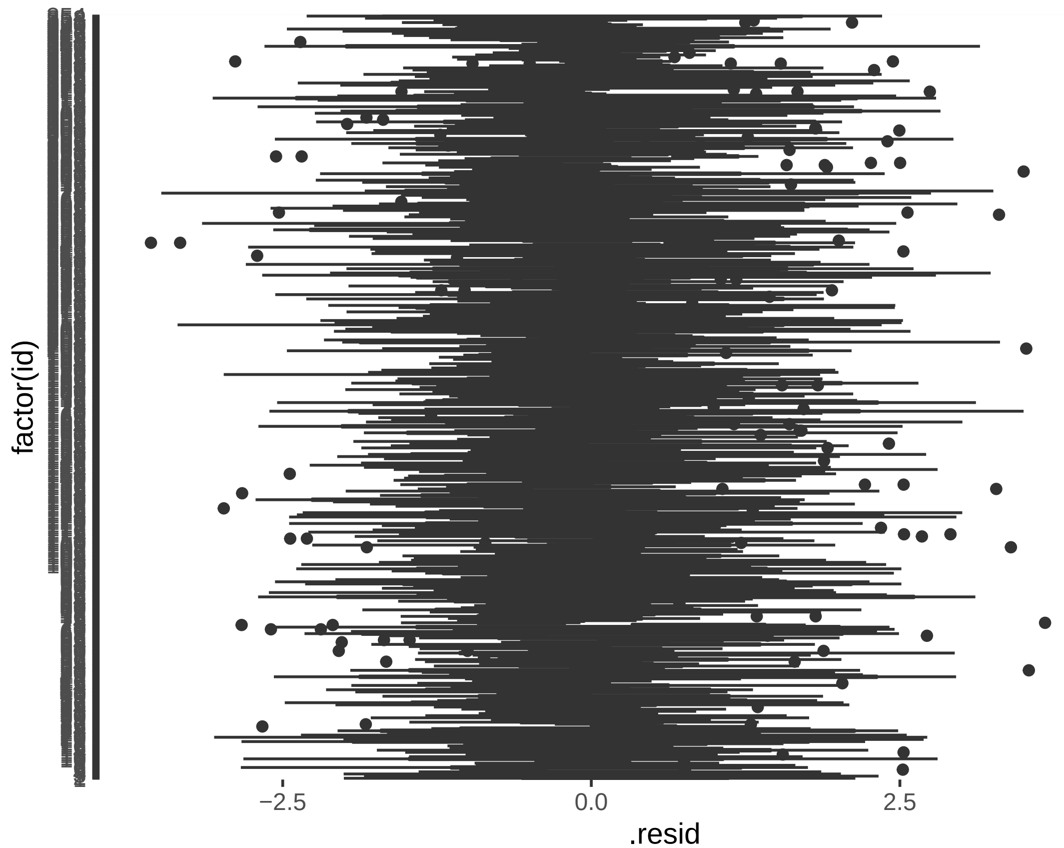
Linearity

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



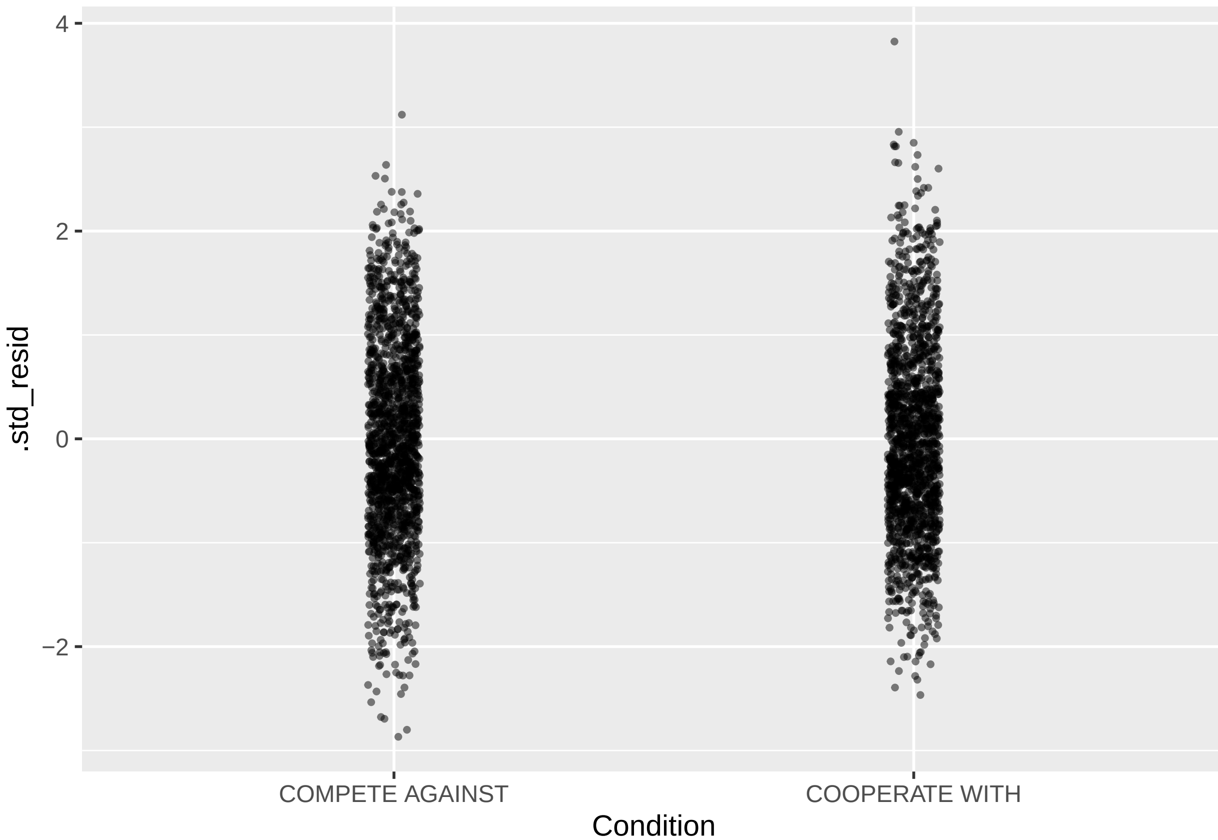
The marginal model plot above shows the outcome variable, objectivism rating, against the predictor perceived agreement. The lines are roughly similar to each other, so there is no need to include extra curvillinear terms.

```
augment(m1) %>%
  ggplot(aes(x = factor(id), y = .resid)) +
  geom_boxplot() +
  coord_flip()
```



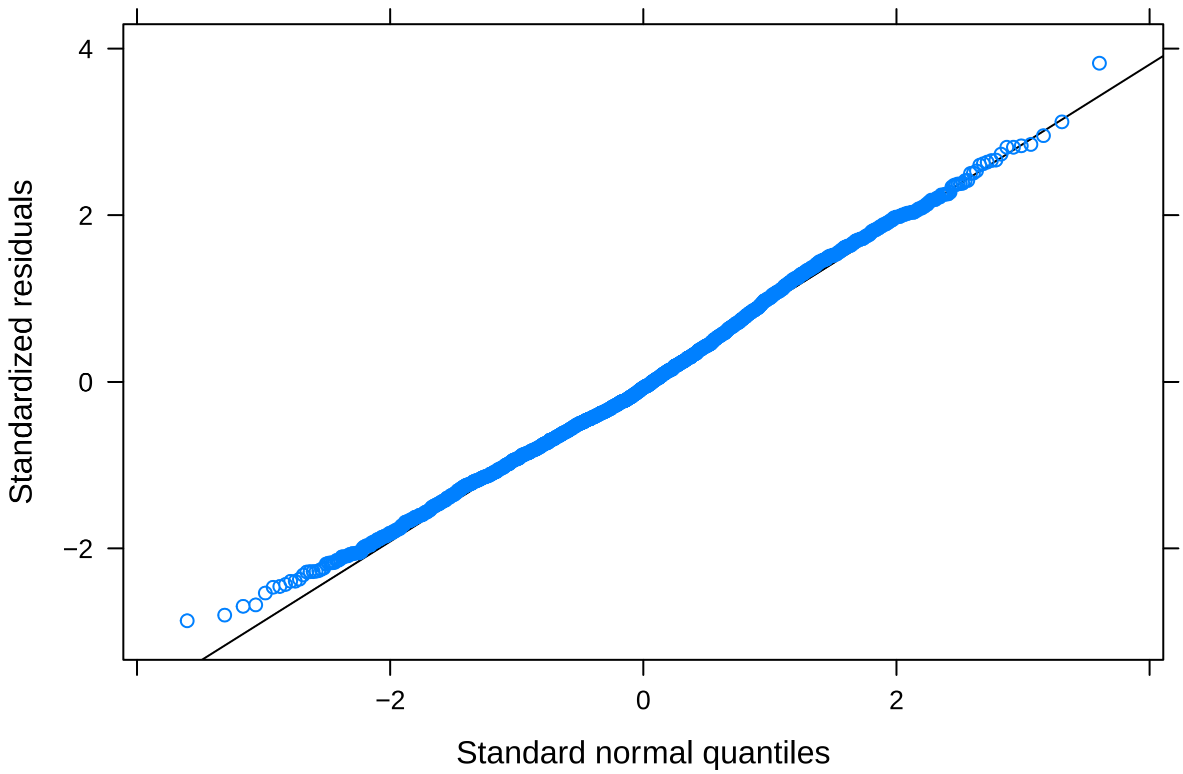
Homogeneity of variance

```
augment(m1) %>%
  mutate(.std_resid = resid(m1, scaled = TRUE)) %>%
  ggplot(aes(x = Condition, y = .std_resid)) +
  # use `geom_jitter` for discrete predictor
  geom_jitter(size = 0.7, alpha = 0.5, width = 0.05)
```



Here, we see that most of the standardized residuals are between -3 and 3, so there are not a lot of outliers. Also, the variability of the residuals looks roughly similar across clusters.

```
library(lattice)  # need this package to use the built-in functions
qqmath(m1)  # just use the `qqmath()` function on the fitted model
```

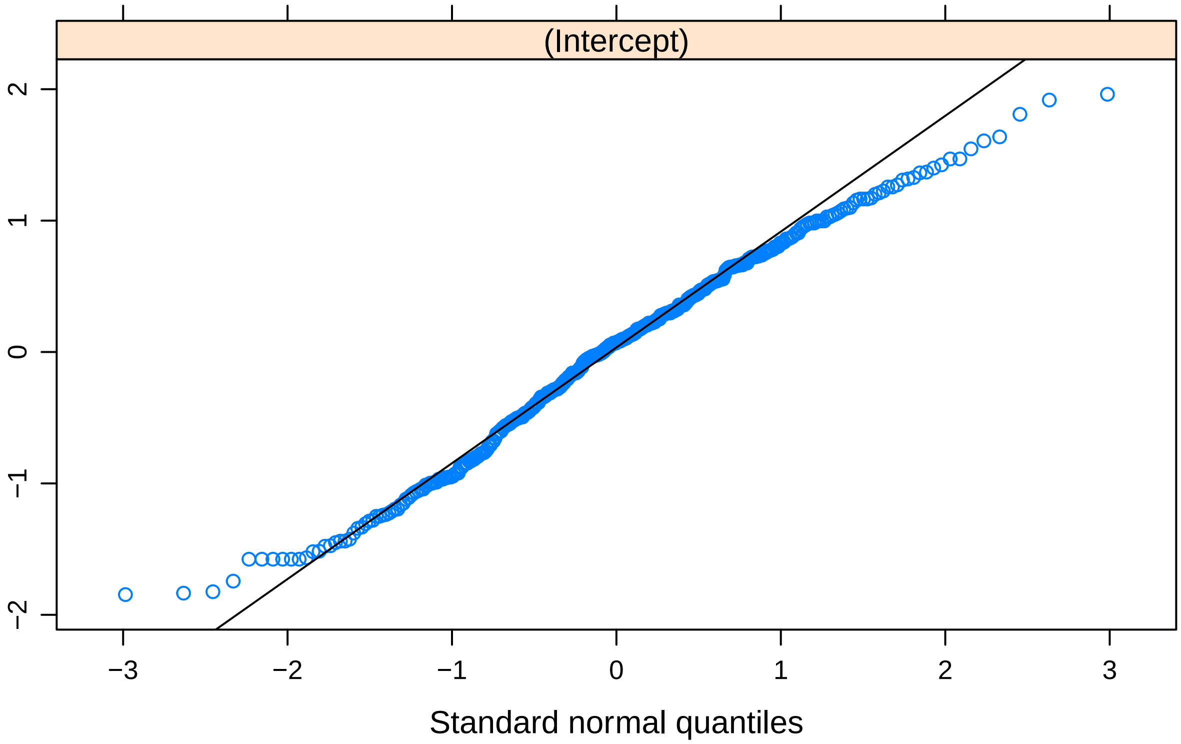


Normality

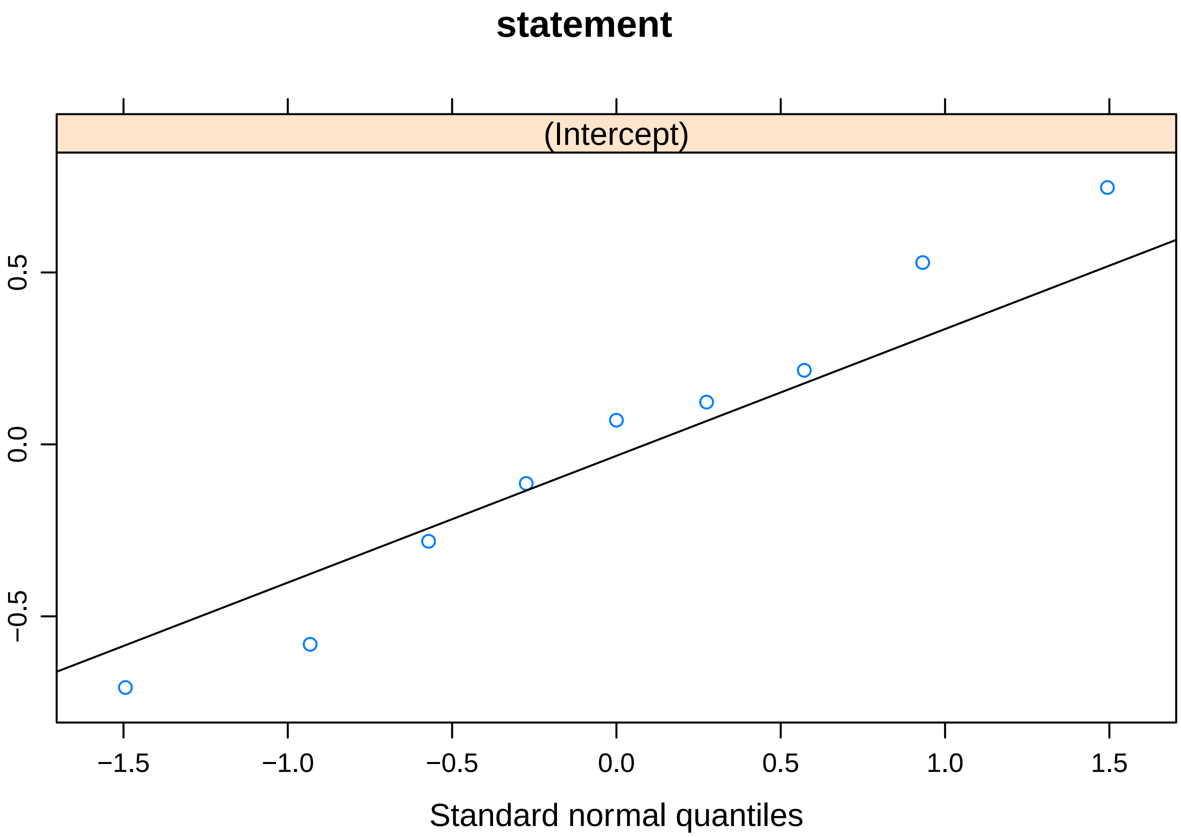
```
qqmath(ranef(m1, condVar = FALSE),
       panel = function(x) {
         panel.qqmath(x)
         panel.qqmathline(x)
       })
```

```
## $id
```

id




```
##
## $statement
```



In the Q-Q plots above, we see the residuals roughly follow the 45-degree line, so normality does not appear to be an issue.

	random-intercept	model 1
Fixed Effects		
(Intercept)	3.070	3.258
	(0.170)	(0.234)
ConditionCOOPERATE WITH		−0.314
		(0.105)
perceived_agreement		−0.013
		(0.064)
Random Effects		
sd__(Intercept)	0.483	0.483
	0.483	0.892
	0.903	0.483
	0.903	0.892
sd__Observation	1.244	1.244
AIC	11094.3	11095.6
BIC	11118.6	11132.0
Log.Lik.	−5543.146	−5541.819
REMLcrit	11086.292	11083.637

Summary table

Testing random slopes We then test random slopes for `Condition` at the `person` level and for `perceived agreement` at the `person` level

```
# Fit a linear growth model with random slope= of time
m1.rs1 <- lmer(objectivism.rating ~ Condition + perceived_agreement + (Condition|statement) + (1|id), da
               control = lmerControl()
)

m1.rs2 <- lmer(objectivism.rating ~ Condition + perceived_agreement + (perceived_agreement|statement) +
)

#test
ranova(m1.rs1)
```

```
## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## objectivism.rating ~ Condition + perceived_agreement + (Condition | statement) + (1 | id)
##                                        npar  logLik   AIC    LRT Df Pr(>Chisq)
## <none>                                    8 -5541.8 11100
## Condition in (Condition | statement)      6 -5541.8 11096   0.04  2     0.9801
## (1 | id)                                  7 -5894.7 11803 705.84  1     <2e-16
##
## <none>
## Condition in (Condition | statement)
## (1 | id)                               ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
ranova(m1.rs2)
```

```
## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## objectivism.rating ~ Condition + perceived_agreement + (perceived_agreement | statement) + (1 | id)
##                                                            npar  logLik   AIC
## <none>                                                        8 -5541.7 11100
## perceived_agreement in (perceived_agreement | statement)     6 -5541.8 11096
## (1 | id)                                                      7 -5894.7 11803
##                                                               LRT Df Pr(>Chisq)
## <none>
## perceived_agreement in (perceived_agreement | statement)   0.16  2     0.9236
## (1 | id)                                                 705.88  1     <2e-16
##
## <none>
## perceived_agreement in (perceived_agreement | statement)
## (1 | id)                                                   ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Neither the random slopes for `Condition` nor 'perceived_agreement' were significant.

Summary We examined the prediction of objectivism ratings using predictors of condition (cooperate or compete) and perceived agreement (how much subjects thought they agreed with the other person on a given item). Main effects for these variables were examined, and condition emerged as a significant predictor. In particular, our model predicts that those in the cooperation condition would report an objectivism rating of 0.31 units lower than those in the competition condition, 95% CI [-0.52, -0.11]. The model also predicts that for every increase in perceived agreement rating, objectism rating would decrease by 0.013 units, 95% CI [-0.14, 0.11], though this effect did not reach significance. Random slopes for subject and item did not reach significance, so we excluded them from our model.