

# Teacher's Job Satisfaction and Workplace Stress: Multilevel Analysis of the TALIS 2018 Italian Sample

Script with output

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```
# Load packages -----
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.0 --
## v ggplot2 3.3.5    v purrr  0.3.4
## v tibble  3.1.6    v dplyr  1.0.8
## v tidyr   1.1.2    v stringr 1.4.0
## v readr   1.4.0    v forcats 0.5.0

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(GGally)

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg      ggplot2

library(ggplot2)
library(DataExplorer)
library(lme4)

## Loading required package: Matrix
##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##   expand, pack, unpack

library(lattice)
library(sjPlot)

## Registered S3 method overwritten by 'parameters':
##   method      from
##   format.parameters_distribution datawizard

library(r2mlm)

## Loading required package: nlme
```

```
##
## Attaching package: 'nlme'

## The following object is masked from 'package:lme4':
##
##      lmList

## The following object is masked from 'package:dplyr':
##
##      collapse

library(broom)
theme_set(theme_bw())

# Load data -----
df4 <- read.csv('../talís_data/df4.csv')

# Glimpse data
glimpse(df4)

## Rows: 3,398
## Columns: 9
## $ IDSCHOOL <int> 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3~
## $ IDTEACH <int> 300101, 300102, 300103, 300104, 300105, 300106, 300107, 30010~
## $ TT3G01 <int> 1, 2, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1~
## $ TCHAGEGR <int> 6, 6, 5, 5, 5, 4, 5, 5, 5, 5, 5, 4, 4, 4, 4, 5, 4, 3, 3, 6, 4~
## $ T3JOBSA <dbl> 14.936916, 11.785688, 13.767235, 13.611691, 15.126234, 12.716~
## $ T3WELS <dbl> 12.672764, 9.108597, 7.937173, 7.596593, 7.744105, 9.303835, ~
## $ T3SELF <dbl> 15.50926, 12.22587, 11.26625, 13.63967, 15.50926, 13.50305, 1~
## $ T3PLACRE <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ SCHLOC <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2~

# Clean data -----
# * Convert to factors -----
# Convert to factor: School ID
df4$IDSCHOOL <- as.factor(df4$IDSCHOOL)
nlevels(df4$IDSCHOOL)

## [1] 186

# Convert to factor: Teacher ID
df4$IDTEACH <- as.factor(df4$IDTEACH)
nlevels(df4$IDTEACH)

## [1] 3398

# Convert to factor: Gender
df4$TT3G01 <- as.factor(df4$TT3G01)
nlevels(df4$TT3G01)

## [1] 2

# Convert to factor: Age group
df4$TCHAGEGR <- as.factor(df4$TCHAGEGR)
nlevels(df4$TCHAGEGR)

## [1] 6

# Convert to factor: Lack of resources
df4$T3PLACRE <- as.factor(df4$T3PLACRE)
```

```

nlevels(df4$T3PLACRE)

## [1] 3

# Convert to factor: School location
df4$SCHLOC <- as.factor(df4$SCHLOC)
nlevels(df4$SCHLOC)

## [1] 3

# Glimpse data
glimpse(df4)

## Rows: 3,398
## Columns: 9
## $ IDSCHOOL <fct> 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3001, 3~
## $ IDTEACH <fct> 300101, 300102, 300103, 300104, 300105, 300106, 300107, 30010~
## $ TT3G01 <fct> 1, 2, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1~
## $ TCHAGEGR <fct> 6, 6, 5, 5, 5, 4, 5, 5, 5, 5, 5, 4, 4, 4, 4, 5, 4, 3, 3, 6, 4~
## $ T3JOBSA <dbl> 14.936916, 11.785688, 13.767235, 13.611691, 15.126234, 12.716~
## $ T3WELS <dbl> 12.672764, 9.108597, 7.937173, 7.596593, 7.744105, 9.303835, ~
## $ T3SELF <dbl> 15.50926, 12.22587, 11.26625, 13.63967, 15.50926, 13.50305, 1~
## $ T3PLACRE <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ SCHLOC <fct> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2~

# * Center lvl-1 predictors WELS & create lvl-2 predictor -----
df4 <- df4 %>%
  group_by(IDSCHOOL) %>%
  # CM = Cluster Mean
  # CMC = Cluster Mean Centered variable
  mutate(T3WELS_CM = mean(T3WELS),
         T3WELS_CMC = T3WELS - T3WELS_CM,
         T3SELF_CM = mean(T3SELF),
         T3SELF_CMC = T3SELF - T3SELF_CM) %>%
  ungroup() %>%
  # Grand mean centering (GMC) of the aggregated variable
  mutate(T3WELS_CM_GMC = T3WELS_CM - mean(T3WELS_CM))

# Check centering results
df4 %>%
  select(T3WELS,
         T3WELS_CM,
         T3WELS_CMC,
         T3WELS_CM_GMC,
         T3SELF_CM,
         T3SELF_CMC) %>%
  summary

```

```

##      T3WELS      T3WELS_CM      T3WELS_CMC      T3WELS_CM_GMC
## Min.   : 7.449   Min.     : 8.244   Min.     :-3.4026   Min.     :-1.08215
## 1st Qu.: 7.937   1st Qu.: 8.940   1st Qu.: -1.2381   1st Qu.: -0.38596
## Median : 8.768   Median : 9.235   Median : -0.4596   Median : -0.09041
## Mean   : 9.326   Mean    : 9.326   Mean    : 0.0000   Mean    : 0.00000
## 3rd Qu.:10.475   3rd Qu.: 9.713   3rd Qu.: 1.0521   3rd Qu.: 0.38726
## Max.   :15.504   Max.    :11.340   Max.    : 6.5836   Max.    : 2.01399
##      T3SELF_CM      T3SELF_CMC

```

```
## Min. :11.57 Min. : -9.69565
## 1st Qu.:12.43 1st Qu.: -1.17782
## Median :12.69 Median : -0.05129
## Mean :12.70 Mean : 0.00000
## 3rd Qu.:13.00 3rd Qu.: 1.15192
## Max. :14.06 Max. : 3.77964
```

```
# Dataset description -----
# How many teachers?
length(unique(df4$IDTEACH))
```

```
## [1] 3398
```

```
# How many schools?
length(unique(df4$IDSCHOOL))
```

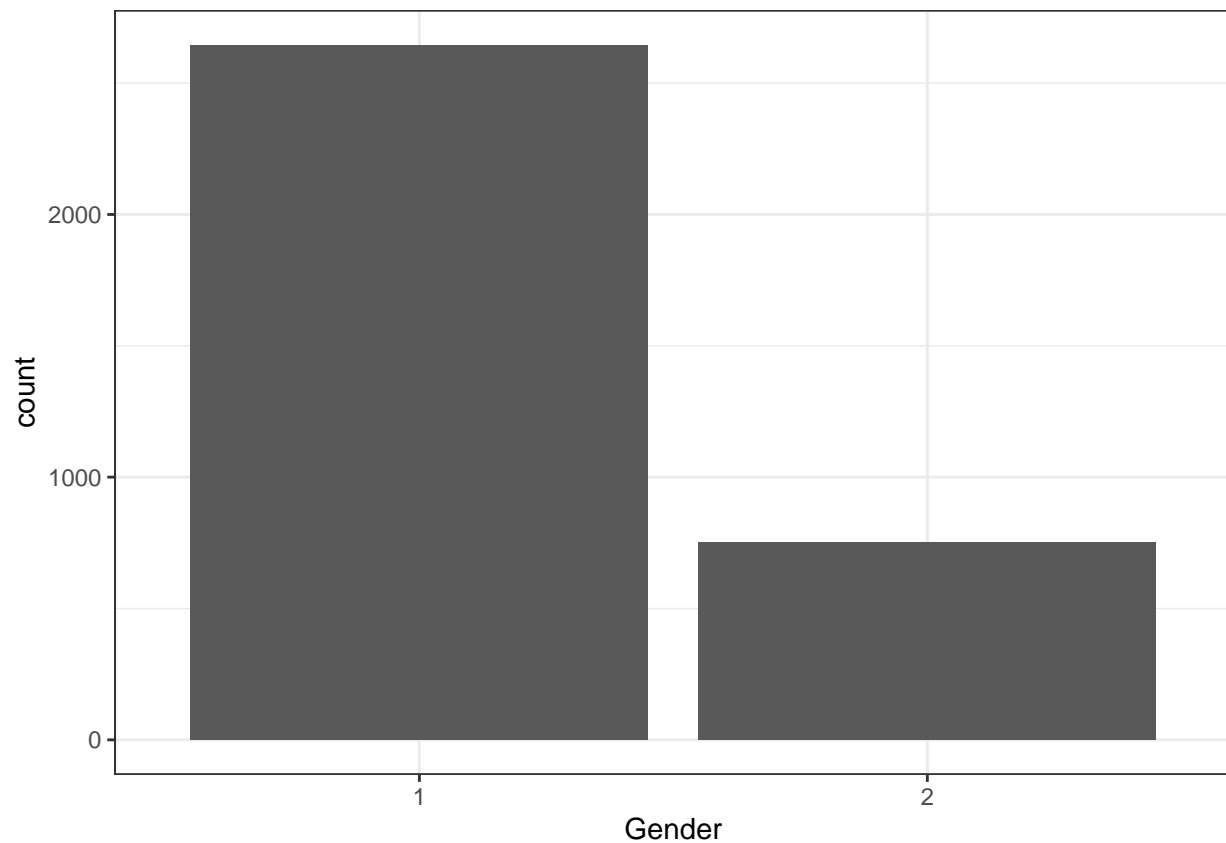
```
## [1] 186
```

```
# Average number of teacher's per school
df4 %>%
  group_by(IDSCHOOL) %>%
  summarise(count = n()) %>%
  mutate(max = max(count),
         min = min(count),
         average = mean(count))
```

```
## # A tibble: 186 x 5
##   IDSCHOOL count   max   min average
##   <fct>    <int> <int> <int>   <dbl>
## 1 3001      19    29     7    18.3
## 2 3002      20    29     7    18.3
## 3 3003      19    29     7    18.3
## 4 3004      14    29     7    18.3
## 5 3005      18    29     7    18.3
## 6 3006      19    29     7    18.3
## 7 3007      20    29     7    18.3
## 8 3008      19    29     7    18.3
## 9 3009      20    29     7    18.3
## 10 3010      14    29     7    18.3
## # ... with 176 more rows
```

```
# Exploratory data analysis -----
# * Univariate analysis -----

# ** Teachers' gender -----
ggplot(df4, aes(x=TT3G01)) +
  geom_bar() +
  labs(x = 'Gender')
```



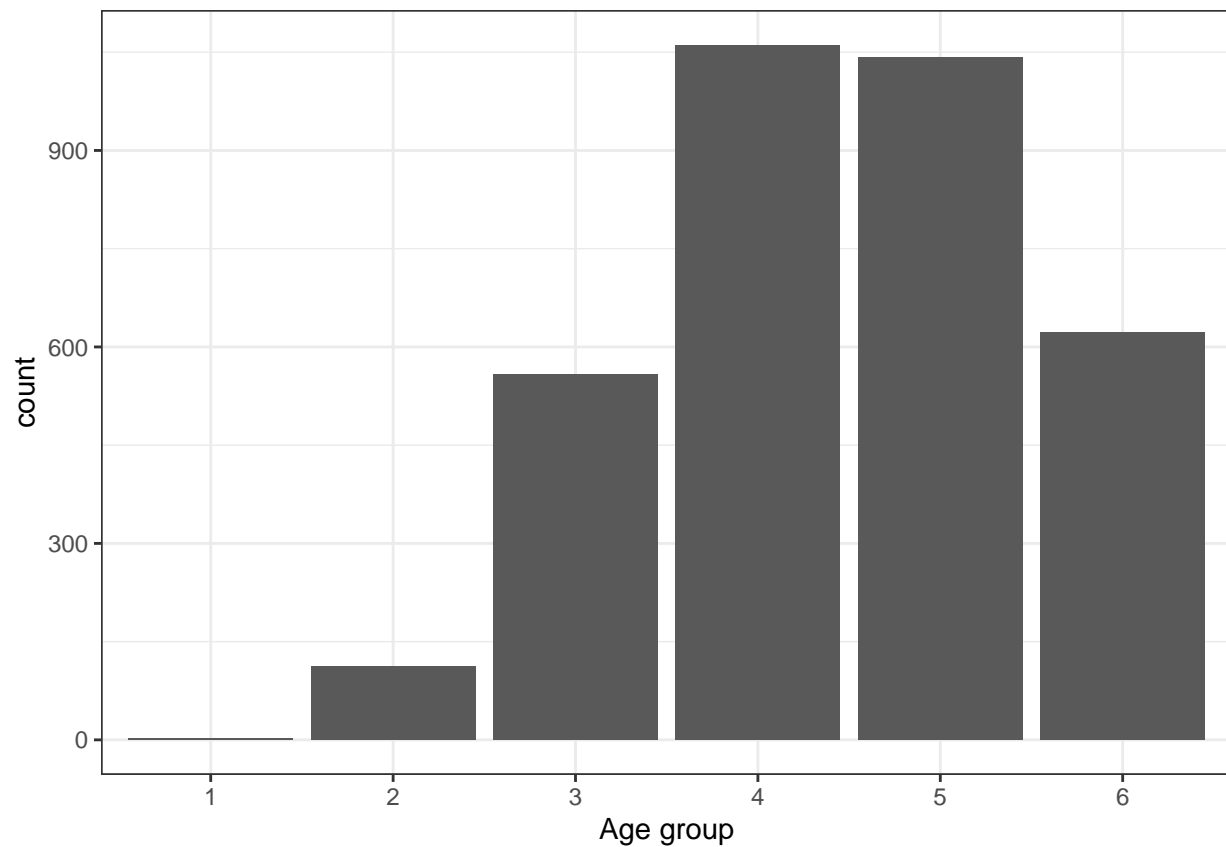
```
gender <- summary(df4$TT3G01)
(per_female <- gender[1]/(gender[1]+gender[2]))
```

```
##          1
## 0.7783991
```

```
(per_male <- gender[2]/(gender[1]+gender[2]))
```

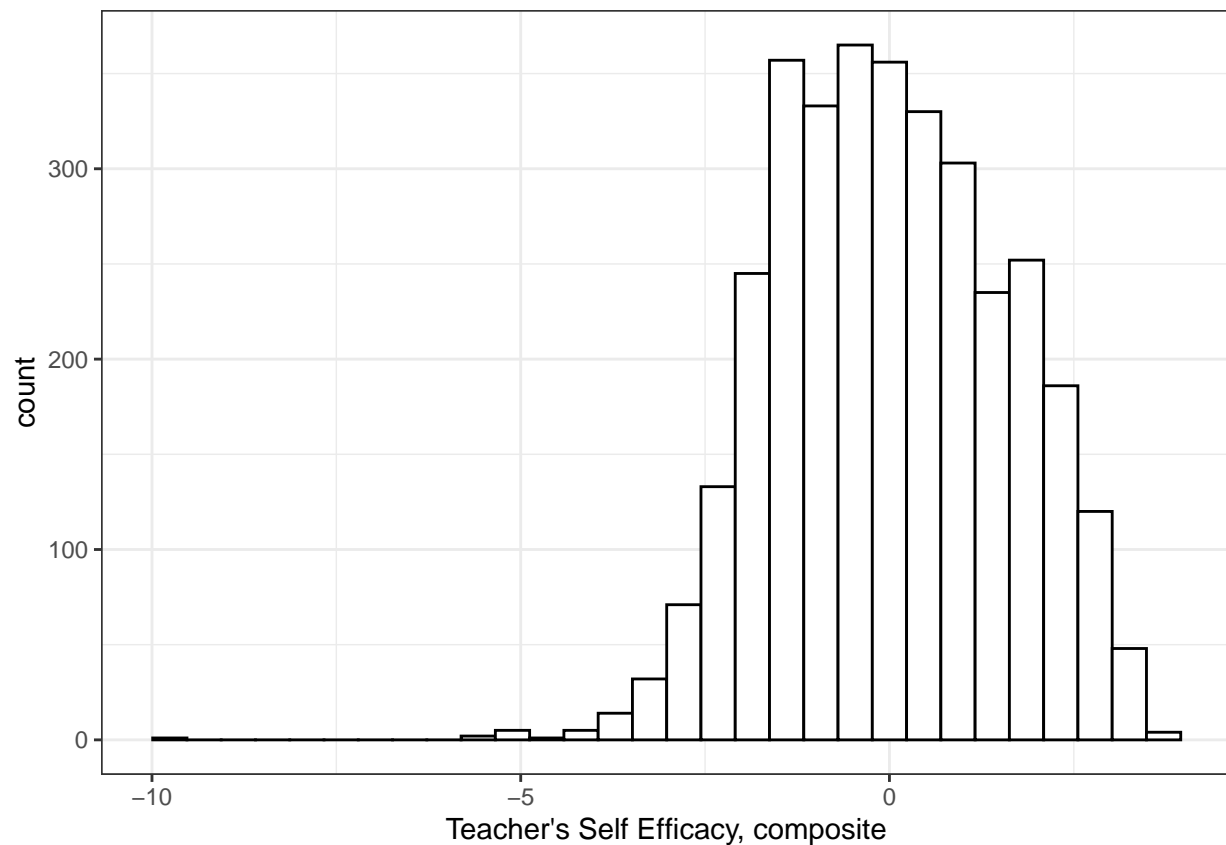
```
##          2
## 0.2216009
```

```
# ** Teachers' age group -----
ggplot(df4, aes(x=TCHAGEGR)) +
  geom_bar() +
  labs(x = 'Age group')
```



```
# ** Teachers' self efficacy -----  
ggplot(df4, aes(x=T3SELF_CMC)) +  
  geom_histogram( colour="black", fill="white") +  
  labs(x = "Teacher's Self Efficacy, composite")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

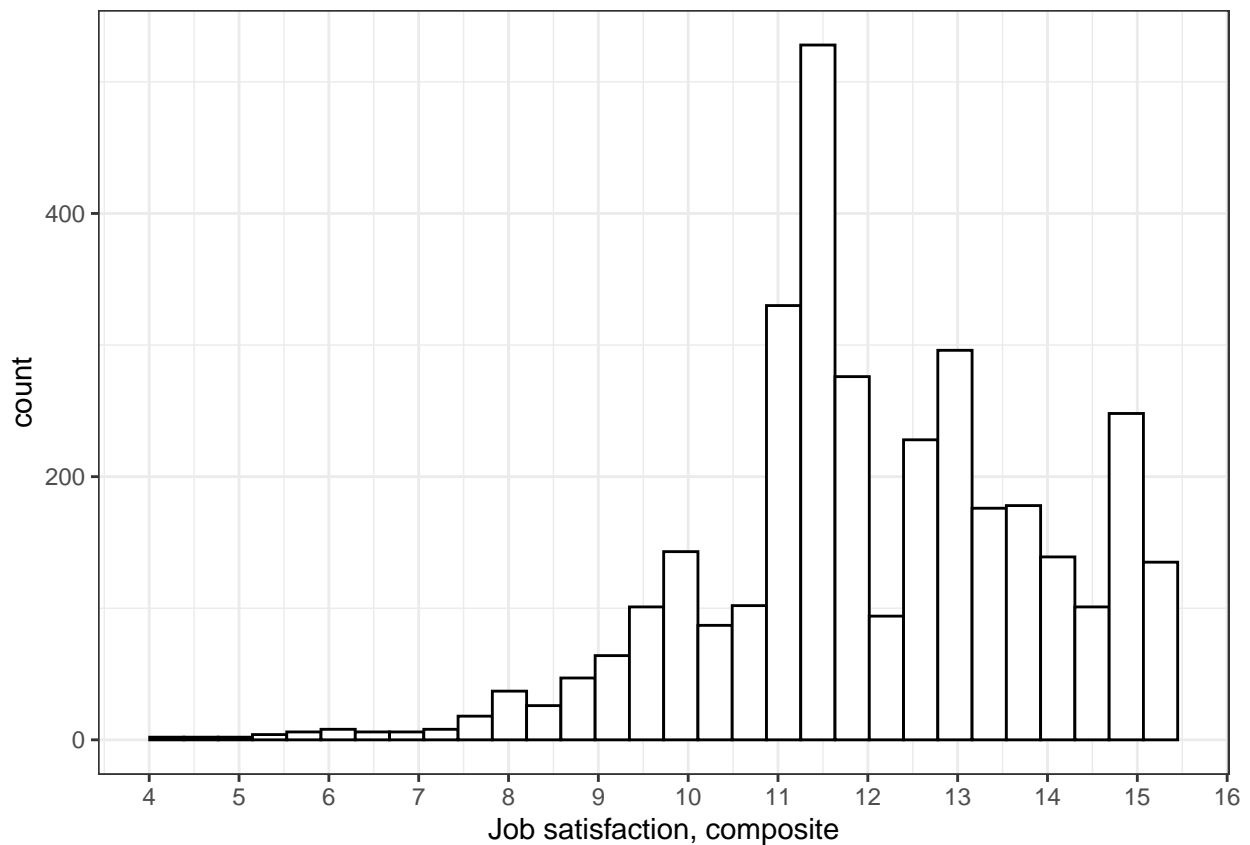


```
summary(df4$T3SELF_CMC)
```

```
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -9.69565 -1.17782 -0.05129  0.00000  1.15192  3.77964
```

```
# ** Job Satisfaction, composite -----
ggplot(df4, aes(x=T3JOBBSA)) +
  geom_histogram( colour="black", fill="white") +
  labs(x = 'Job satisfaction, composite') +
  scale_x_continuous(breaks = seq(1:17))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



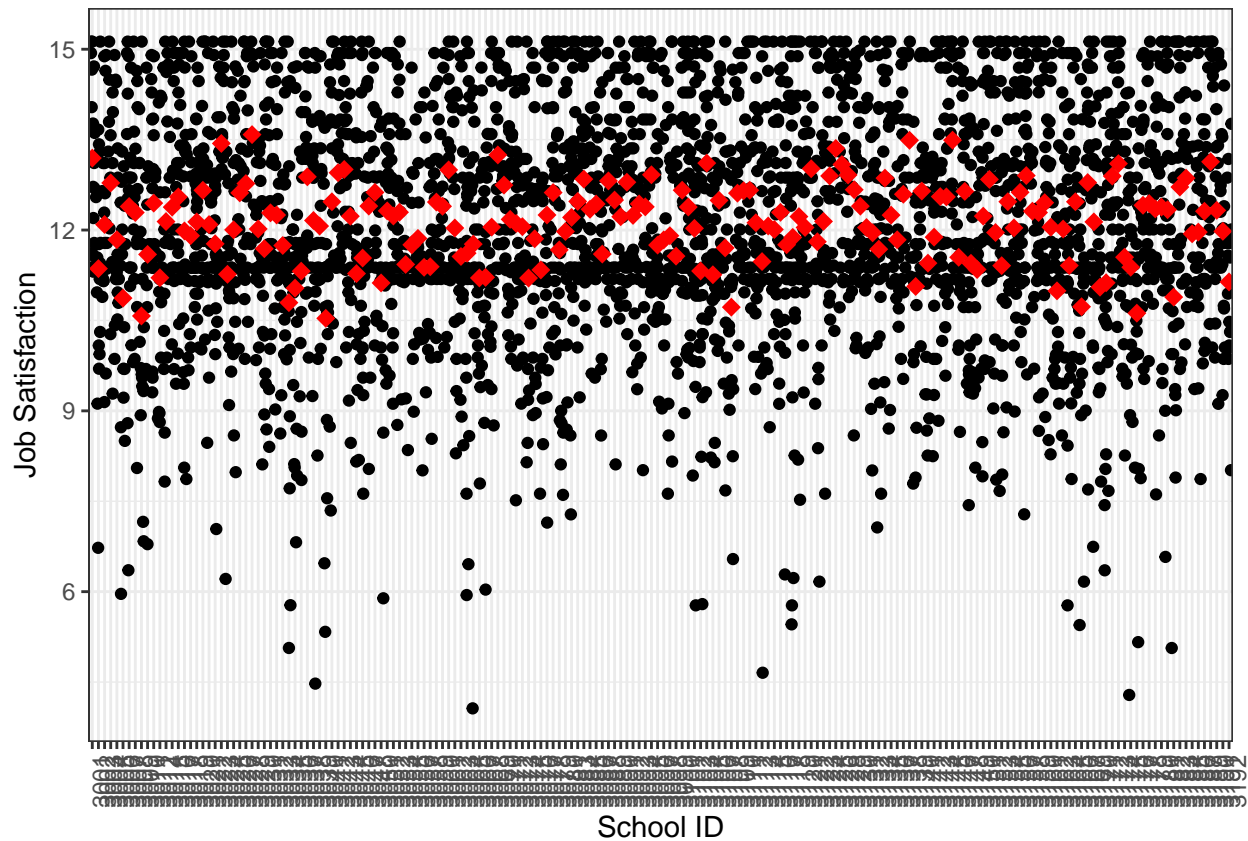
```
summary(df4$T3JOBSA)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      4.064  11.154  11.819  12.087  13.369  15.126
```

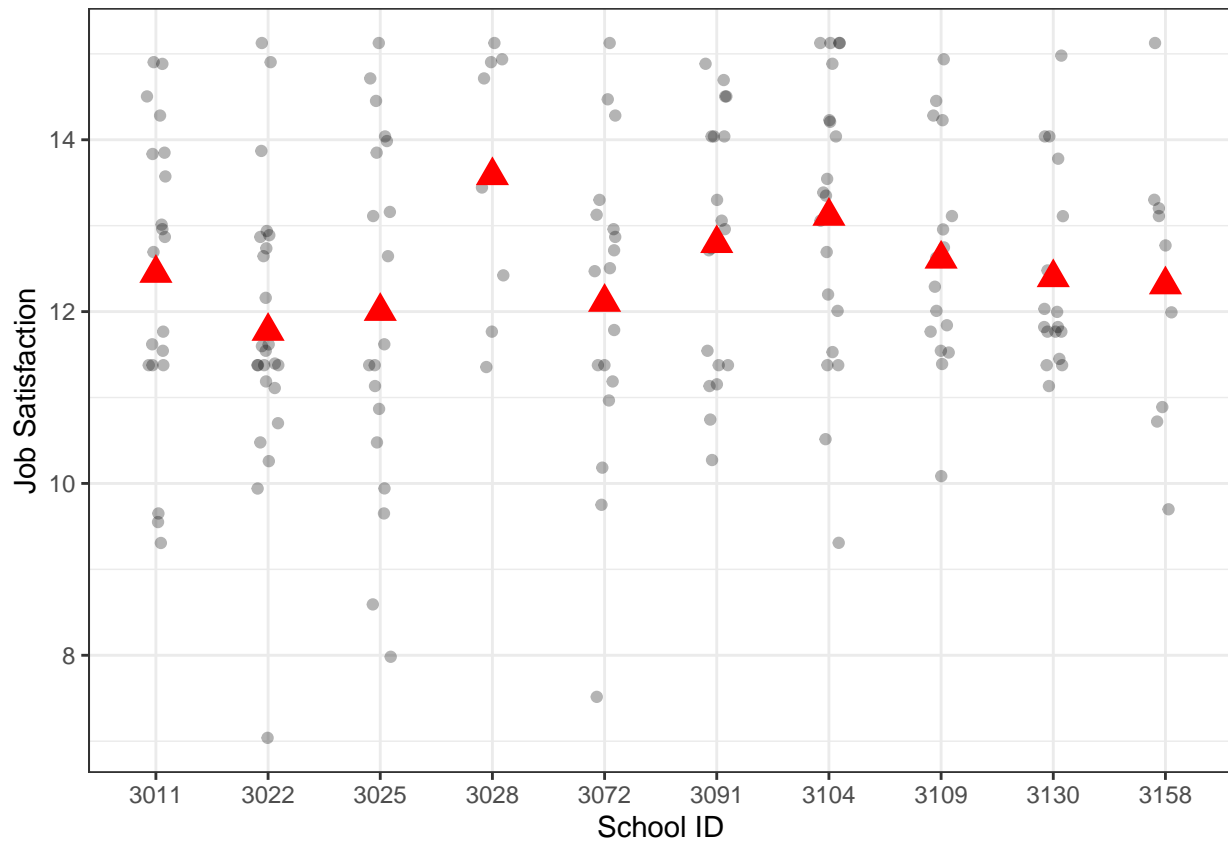
```
# Basic stripchart
```

```
ggplot(df4, aes(x=IDSCHOOL, y=T3JOBSA)) +
  geom_jitter() +
  stat_summary(fun=mean, geom="point", shape=18,
               size=3, color="red") +
  labs(y = "Job Satisfaction",
       x = "School ID") +
  theme(axis.text.x = element_text(angle = 90))
```



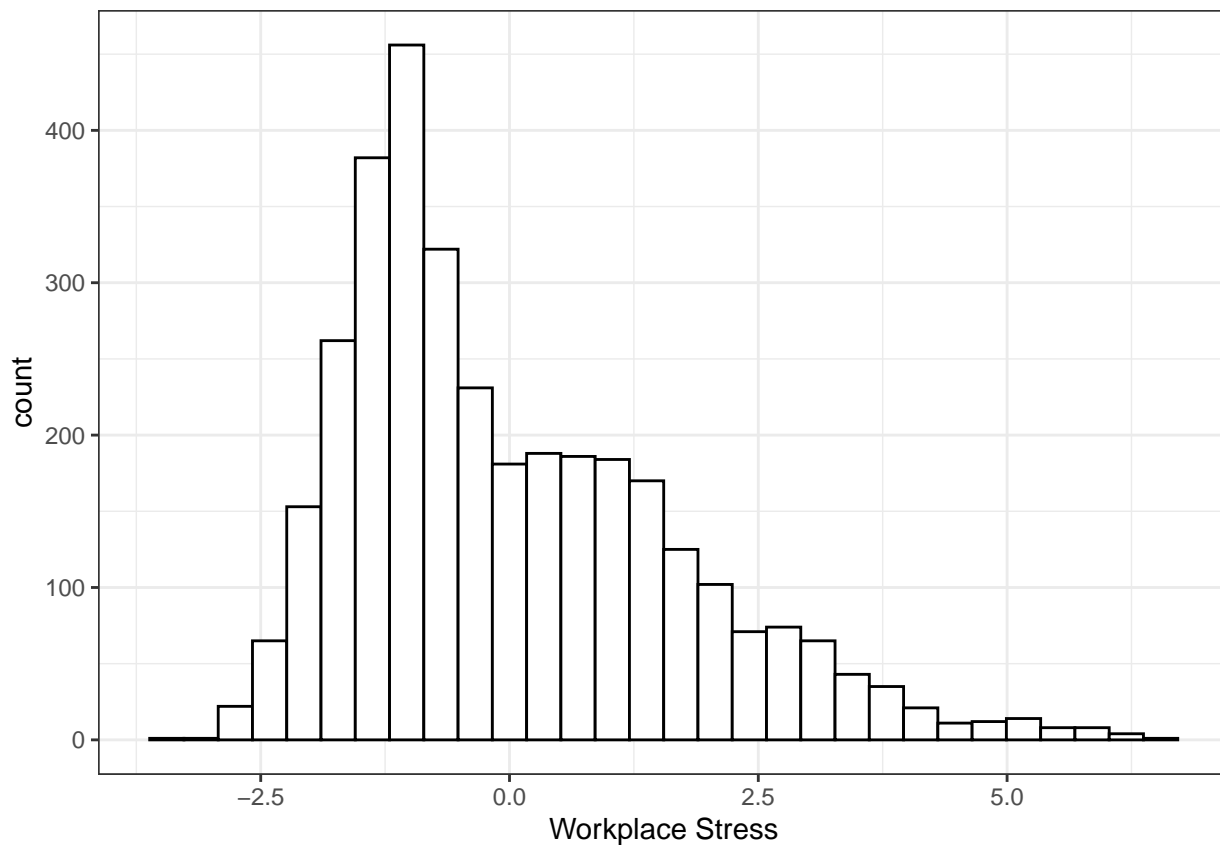


```
# Show variation across a subset of ten schools
set.seed(1994)
random_id <- sample(unique(df4$IDSCHOOL), size = 10)
(p_subset <- df4 %>%
  filter(IDSCHOOL %in% random_id) %>% # select only 10 schools
  ggplot(aes(x = IDSCHOOL, y = T3JOBSA )) +
  geom_jitter(height = 0, width = 0.1, alpha = 0.3) +
  labs(y = "Job Satisfaction",
       x = "School ID") +
  # Add school means
  stat_summary(
    fun = "mean",
    geom = "point",
    col = "red",
    shape = 17,
    # use triangles
    size = 4
  ) # make them larger
)
```



```
# ** Workplace stress -----
ggplot(df4, aes(x=T3WELS_CMC)) +
  geom_histogram( colour="black", fill="white") +
  labs(x = 'Workplace Stress')
```

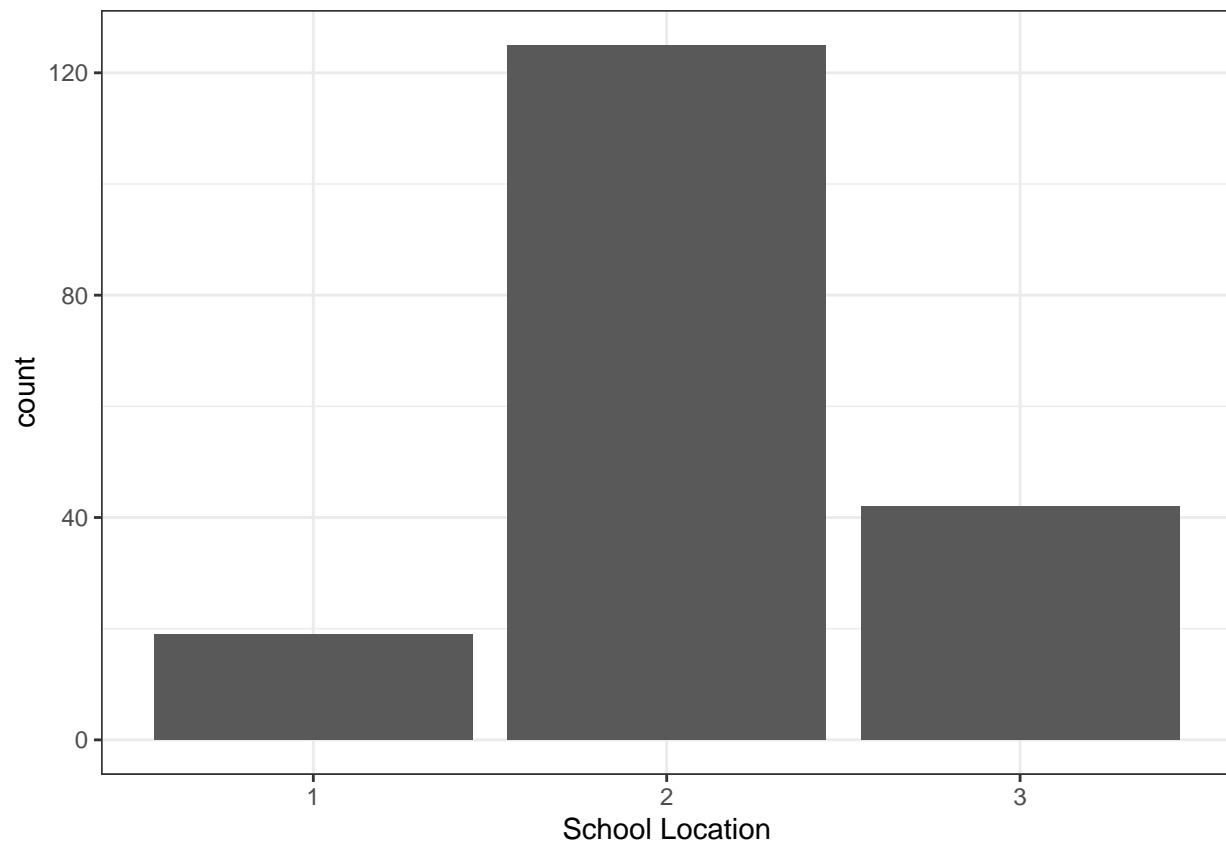
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
summary(df4$T3WELS_CMC)
```

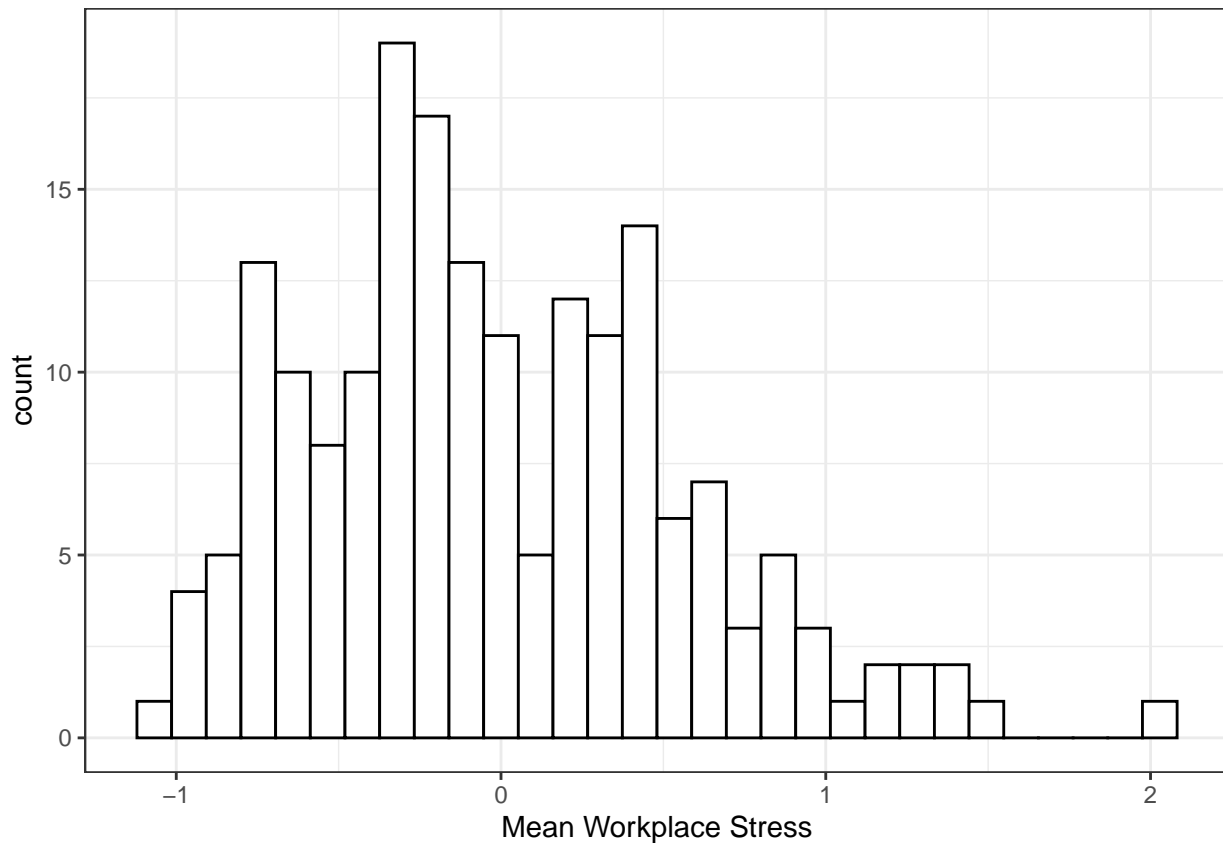
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -3.4026 -1.2381 -0.4596  0.0000  1.0521  6.5836
```

```
# ** School location -----
df4 %>%
  group_by(IDSCHOOL) %>%
  filter(row_number()==1) %>%
  ggplot(aes(x=SCHLOC)) +
  geom_bar() +
  labs(x = "School Location")
```



```
# ** Mean workplace stress -----
df4 %>%
  group_by(IDSCHOOL) %>%
  filter(row_number()==1) %>%
  ggplot(aes(x=T3WELS_CM_GMC)) +
  geom_histogram( colour="black", fill="white") +
  labs(x = 'Mean Workplace Stress')

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
summary(df4$T3WELS_CM_GMC)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.08215 -0.38596 -0.09041  0.00000  0.38726  2.01399
```

```
# * Bivariate analysis -----
```

```
# ** Workplace Stress vs Job Satisfaction -----
```

```
# Overall regression line
```

```
ggplot(data = df4,
       aes(x = T3WELS_CMC,
           y = T3JOBSA,
           col = IDSCHOOL)) +
  geom_point(size = 1.2,
             alpha = .8) +
  geom_smooth(method = lm,
             se = FALSE,
             col = "black",
             size = .5,
             alpha = .8) +
  theme(legend.position = "none") +
  labs(title = "Job Satisfaction vs. Workplace Stress",
       subtitle = "Colored by school",
       x = "Workplace Stress",
       y = "Job Satisfaction")
```

```
## `geom_smooth()` using formula 'y ~ x'
```

## Job Satisfaction vs. Workplace Stress

Colored by school



```
# One regression line per school
ggplot(data = df4,
  aes(x = T3WELS_CMC,
    y = T3JOBSA,
    col = IDSCHOOL,
    group = IDSCHOOL))+
  geom_point(size = 1.2,
    alpha = .8)+
  geom_smooth(method = lm,
    se = FALSE,
    size = .5,
    alpha = .8)+
  theme(legend.position = "none")+
  labs(title = "Job Satisfaction vs. Workplace Stress",
    subtitle = "Colored by school",
    x = "Workplace Stress",
    y = "Job Satisfaction")
```

```
## `geom_smooth()` using formula 'y ~ x'
```

## Job Satisfaction vs. Workplace Stress

Colored by school



```
# Unconditional random intercept model -----
modell1 <- lmer(T3JOBSA ~ 1 + (1 | IDSCHOOL), data = df4)
# Summarize results
summary(modell1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: T3JOBSA ~ 1 + (1 | IDSCHOOL)
## Data: df4
##
## REML criterion at convergence: 13765.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.3803 -0.5639 -0.0489  0.6991  2.1757
##
## Random effects:
## Groups Name Variance Std.Dev.
## IDSCHOOL (Intercept) 0.217 0.4658
## Residual 3.218 1.7938
## Number of obs: 3398, groups: IDSCHOOL, 186
##
## Fixed effects:
## Estimate Std. Error t value
```

```
# Profile likelihood confidence intervals
confint(modell1)
```

```

## Computing profile confidence intervals ...

##           2.5 %    97.5 %
## .sig01      0.3793898  0.5547561
## .sigma      1.7508008  1.8385610
## (Intercept) 12.0081355 12.1897162

# Testing for "school effects"
# Null single level model
fit <- lm(T3JOBSA ~ 1, data = df4)
# Likelihood ratio
(ll_simple<-logLik(fit)[1])

## [1] -6916.383

(ll_complex <-logLik(model1)[1])

## [1] -6882.907
(LR <- -2*ll_simple-(-2*ll_complex)) # 1df because only 1 parameter difference

## [1] 66.95039
(pval_lr <- (pchisq(LR, df=1, lower.tail = FALSE)/2))

## [1] 1.392129e-16

# * ICC -----
variance_components <- as.data.frame(VarCorr(model1))
(between_var <- variance_components$vcov[1])

## [1] 0.2169971
(within_var <- variance_components$vcov[2])

## [1] 3.217665
(icc <- between_var / (between_var + within_var))

## [1] 0.06317859

# * Empirical Bayes estimates -----

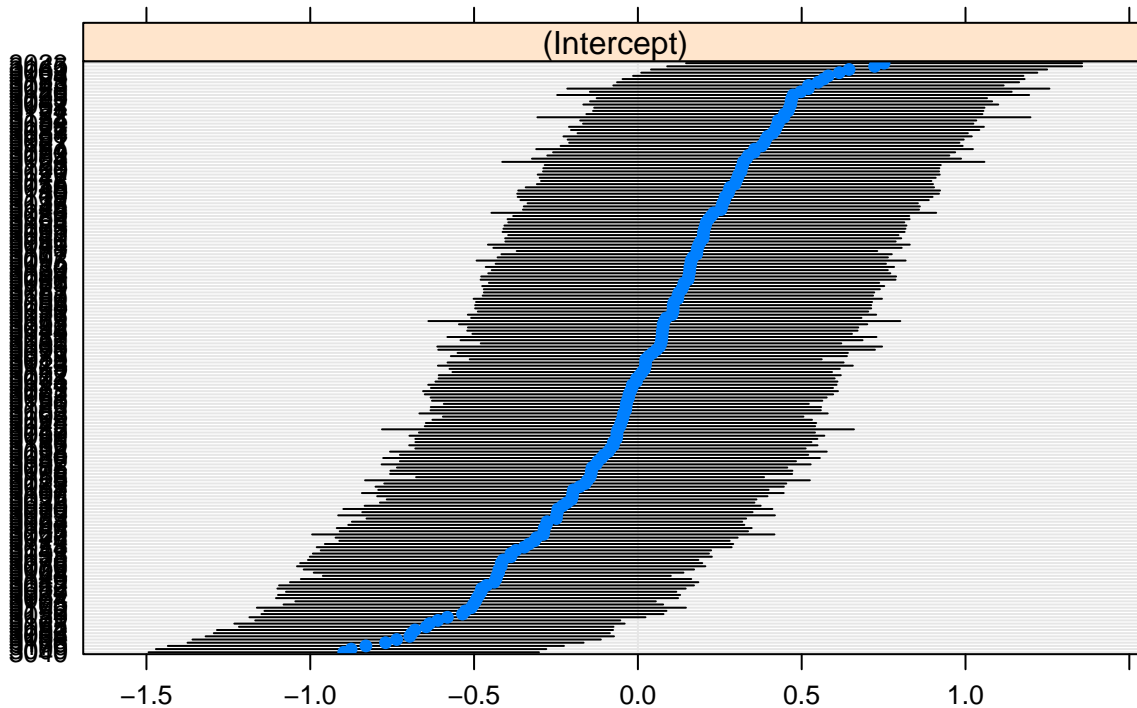
dotplot(ranef(model1, condVar = TRUE))

## $IDSCHOOL

```



## IDSCHOOL



```
# * Design effect -----
cluster_size <- df4 %>%
  group_by(IDSCHOOL) %>%
  summarise(count = n())
(average_cluster_size <- mean(cluster_size$count))
```

```
## [1] 18.26882
```

```
(design_effect <- 1 + (average_cluster_size - 1) * icc)
```

```
## [1] 2.091019
```

```
# Effective sample size
(n_eff <- length(df4$IDTEACH)/design_effect)
```

```
## [1] 1625.045
```

```
# Add lvl-2 predictor: mean workplace stress -----
model2_pre <- lmer(T3JOBSA ~ T3WELS_CM_GMC + (1 | IDSCHOOL), data = df4)
# Summarize results
summary(model2_pre)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: T3JOBSA ~ T3WELS_CM_GMC + (1 | IDSCHOOL)
## Data: df4
##
## REML criterion at convergence: 13702.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.4256 -0.5753 -0.0469  0.7082  2.4371
```

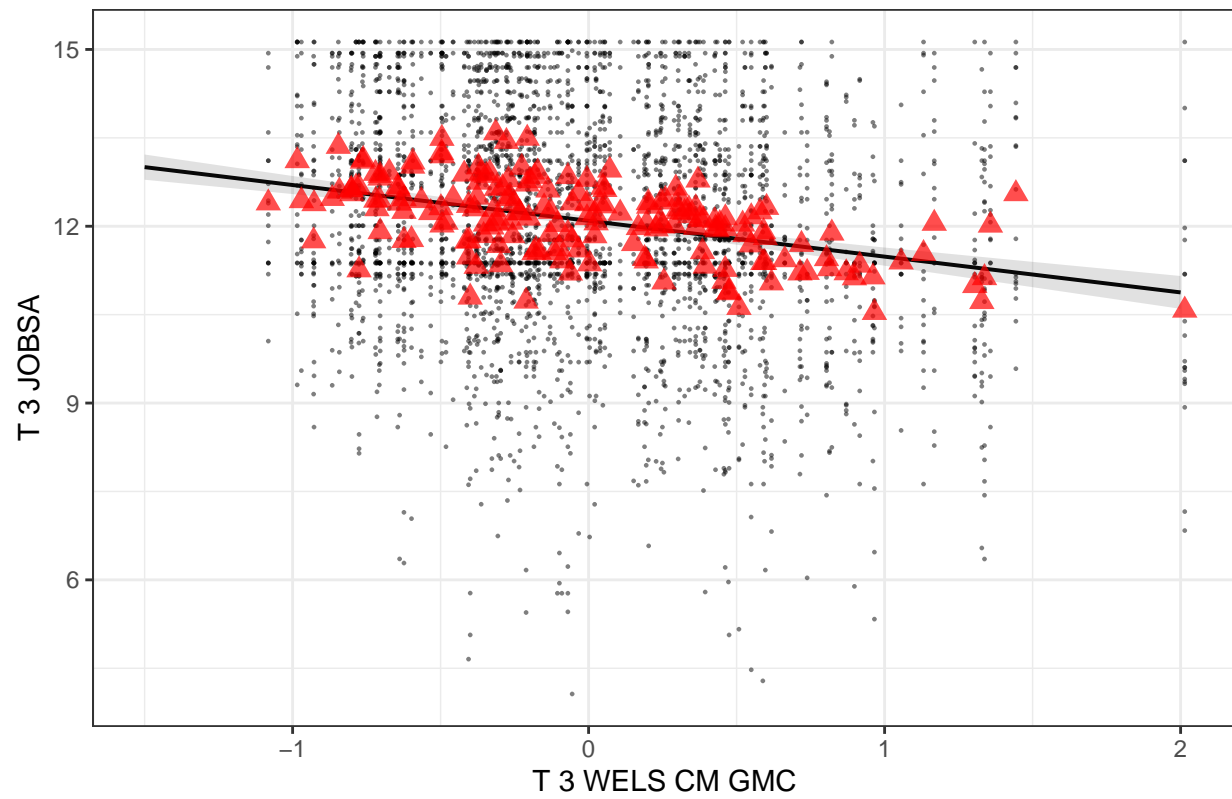
```
##
## Random effects:
##   Groups   Name      Variance Std.Dev.
##   IDSCHOOL (Intercept) 0.1008   0.3176
##   Residual          3.2164   1.7934
## Number of obs: 3398, groups:  IDSCHOOL, 186
##
## Fixed effects:
##               Estimate Std. Error t value
## (Intercept)   12.09210    0.03875 312.062
## T3WELS_CM_GMC -0.60739    0.06829  -8.895
##
## Correlation of Fixed Effects:
##               (Intr)
## T3WELS_CM_G 0.007

# Likelihood-based confidence intervals for fixed effects
confint(model2_pre)

## Computing profile confidence intervals ...

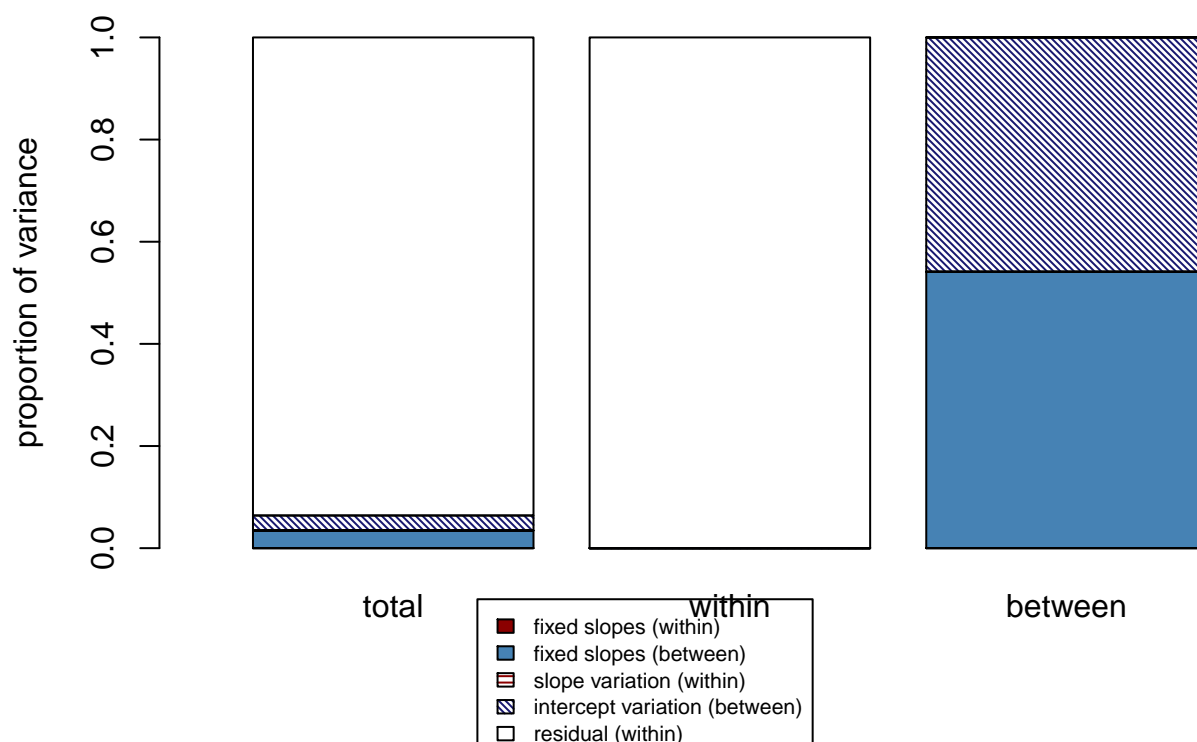
##               2.5 %    97.5 %
## .sig01         0.2194844 0.4033291
## .sigma         1.7504740 1.8381819
## (Intercept)   12.0162400 12.1681472
## T3WELS_CM_GMC -0.7412955 -0.4736586

# Plot
sjPlot::plot_model(model2_pre,
  type = "pred",
  terms = "T3WELS_CM_GMC",
  show.data = TRUE,
  title = "",
  dot.size = 0.5) +
  stat_summary(data = df4, aes(x = T3WELS_CM_GMC, y = T3JOBSA),
    fun = mean, geom = "point",
    col = "red",
    shape = 17,
    # use triangles
    size = 3,
    alpha = 0.7)
```



```
# Proportion of variance explained
## Use Rights & Sterba (2019)
r2mlm: r2mlm(model2_pre)
```

## Decomposition



```
## $Decompositions
##          total          within between
## fixed, within    0          0      NA
## fixed, between 0.0346214414535156 NA    0.541221947359481
## slope variation 0          0      NA
## mean variation 0.0293475857125612 NA    0.458778052640519
## sigma2          0.936030972833923 1      NA
##
```

```
## $R2s
##          total          within between
## f1 0          0      NA
## f2 0.0346214414535156 NA    0.541221947359481
## v 0          0      NA
## m 0.0293475857125612 NA    0.458778052640519
## f 0.0346214414535156 NA    NA
## fv 0.0346214414535156 0      NA
## fvm 0.0639690271660768 NA    NA
```

```
# Add lvl-1 predictor: workplace stress (between-within model) -----
model2 <- lmer(T3JOBSA ~ T3WELS_CMC+ T3WELS_CM_GMC + (1 | IDSCHOOL), data = df4)
# Summarize results
summary(model2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: T3JOBSA ~ T3WELS_CMC + T3WELS_CM_GMC + (1 | IDSCHOOL)
## Data: df4
##
## REML criterion at convergence: 13031.2
##
```

```

## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.3598 -0.6744 -0.0129  0.7310  3.4977
##
## Random effects:
##   Groups   Name      Variance Std.Dev.
## IDSCHOOL (Intercept) 0.1342   0.3663
## Residual                2.6055   1.6142
## Number of obs: 3398, groups:  IDSCHOOL, 186
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  12.09396    0.03876 312.019
## T3WELS_CMC    -0.45864    0.01670 -27.469
## T3WELS_CM_GMC -0.60916    0.06833  -8.915
##
## Correlation of Fixed Effects:
##              (Intr) T3WELS_CMC
## T3WELS_CMC    0.000
## T3WELS_CM_G  0.009  0.000

```

```

# Likelihood-based confidence intervals for fixed effects
confint(model2)

```

```

## Computing profile confidence intervals ...

##              2.5 %      97.5 %
## .sig01         0.2856582  0.4428430
## .sigma         1.5752431  1.6541868
## (Intercept)   12.0180716 12.1700097
## T3WELS_CMC     -0.4913706 -0.4259122
## T3WELS_CM_GMC -0.7431460 -0.4753427

```

```

# * Contextual effect -----
-0.60916 - (-0.45864)

```

```

## [1] -0.15052

```

```

## Look at the reparametrized model
model2_context <- lmer(T3JOBSA ~ T3WELS + T3WELS_CM_GMC + (1 | IDSCHOOL), data = df4)
summary(model2_context)

```

```

## Linear mixed model fit by REML ['lmerMod']
## Formula: T3JOBSA ~ T3WELS + T3WELS_CM_GMC + (1 | IDSCHOOL)
##   Data: df4
##
## REML criterion at convergence: 13031.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.3598 -0.6744 -0.0129  0.7310  3.4977
##
## Random effects:
##   Groups   Name      Variance Std.Dev.
## IDSCHOOL (Intercept) 0.1342   0.3663
## Residual                2.6055   1.6142
## Number of obs: 3398, groups:  IDSCHOOL, 186

```

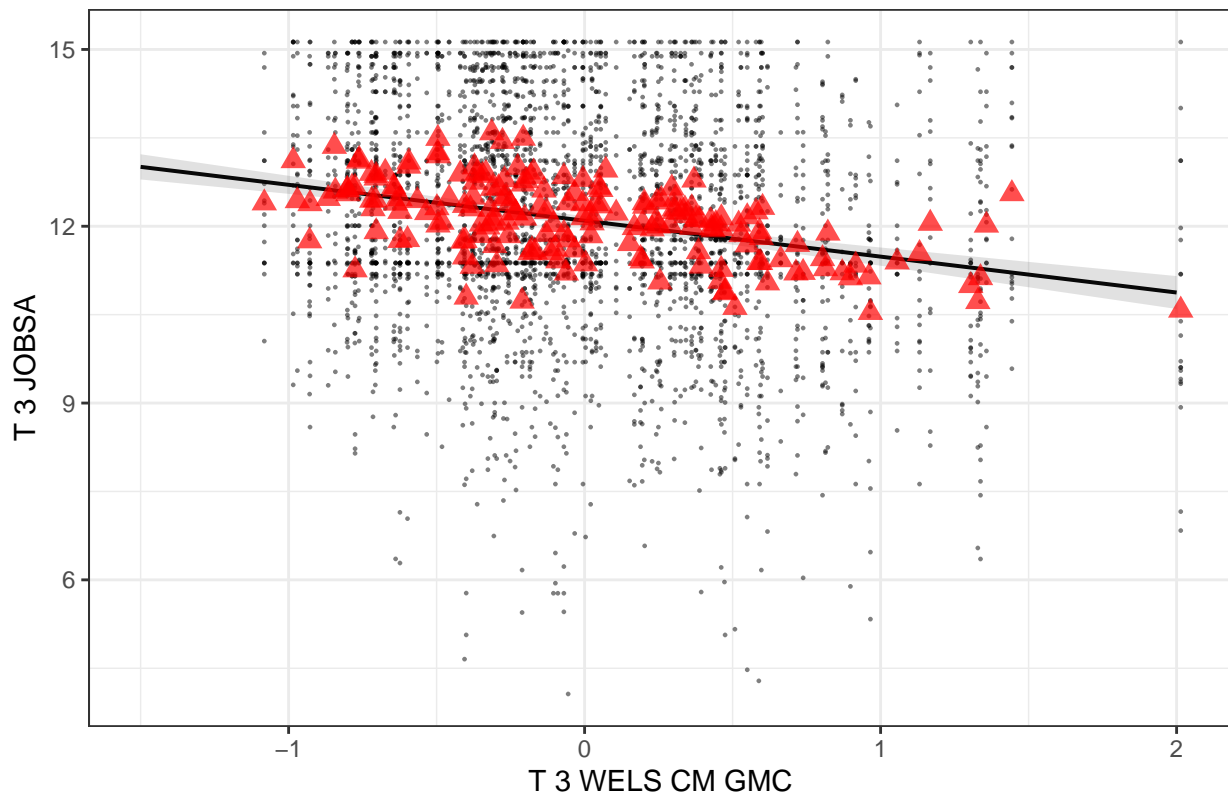
```
##
## Fixed effects:
##           Estimate Std. Error t value
## (Intercept)  16.37113    0.16046  102.03
## T3WELS       -0.45864    0.01670  -27.47
## T3WELS_CM_GMC -0.15052    0.07034   -2.14
##
## Correlation of Fixed Effects:
##           (Intr) T3WELS
## T3WELS      -0.970
## T3WELS_CM_G  0.233 -0.237

# Likelihood-based confidence intervals for fixed effects
confint(model2_context )

## Computing profile confidence intervals ...

##           2.5 %      97.5 %
## .sig01      0.2856582  0.44284296
## .sigma      1.5752431  1.65418680
## (Intercept) 16.0565977 16.68547926
## T3WELS      -0.4913706 -0.42591222
## T3WELS_CM_GMC -0.2883959 -0.01278995

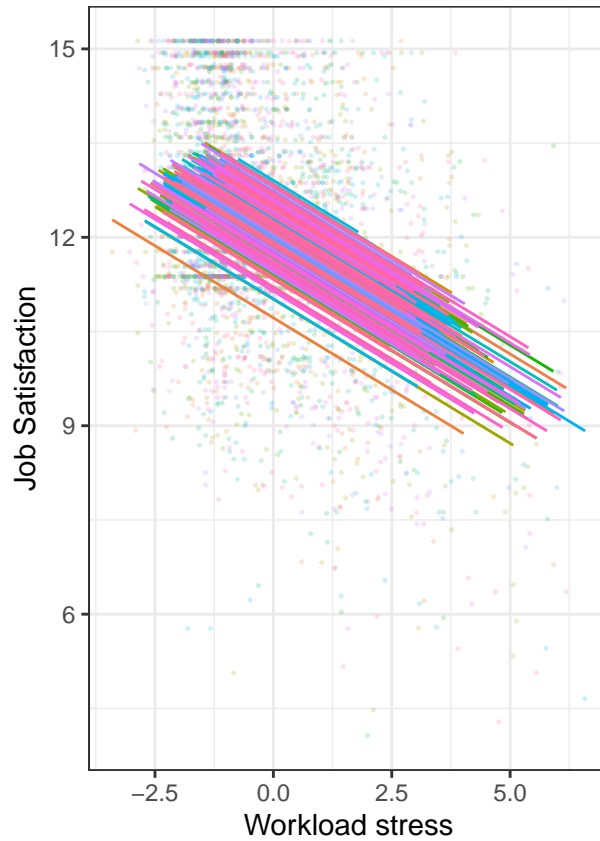
# * Visualizing the difference -----
sjPlot::plot_model(model2,
                    type = "pred",
                    terms = "T3WELS_CM_GMC",
                    show.data = TRUE,
                    title = "",
                    dot.size = 0.5) +
  stat_summary(data = df4, aes(x = T3WELS_CM_GMC, y = T3JOBSA),
              fun = mean, geom = "point",
              col = "red",
              shape = 17,
              # use triangles
              size = 3,
              alpha = 0.7)
```



```
# Create a common base graph
pbase <- augment(model12, data = df4) %>%
  ggplot(aes(x = T3WELS_CM_GMC, y = T3JOBSA, color = factor(IDSCHOOL))) +
  # Add points
  geom_point(size = 0.2, alpha = 0.2) +
  labs(y = "Job Satisfaction") +
  # Suppress legend
  guides(color = "none")
# Lv-1 effect
p1 <- pbase +
  # Add within-cluster lines
  geom_smooth(aes(y = .fitted),
    method = "lm", se = FALSE, size = 0.5) +
  labs(x = "Workload stress")
# Lv-2 effect
p2 <- pbase +
  # Add group means
  stat_summary(aes(x = T3WELS_CM_GMC, y = .fitted),
    fun = mean,
    geom = "point",
    shape = 17,
    # use triangles
    size = 2.5) +
  # Add between coefficient
  geom_smooth(aes(x = T3WELS_CM_GMC, y = .fitted),
    method = "lm", se = FALSE,
    color = "black") +
  labs(x = "Workload stress")
```

```
# Put the two graphs together (need the gridExtra package)
gridExtra::grid.arrange(p1, p2, ncol = 2)
```

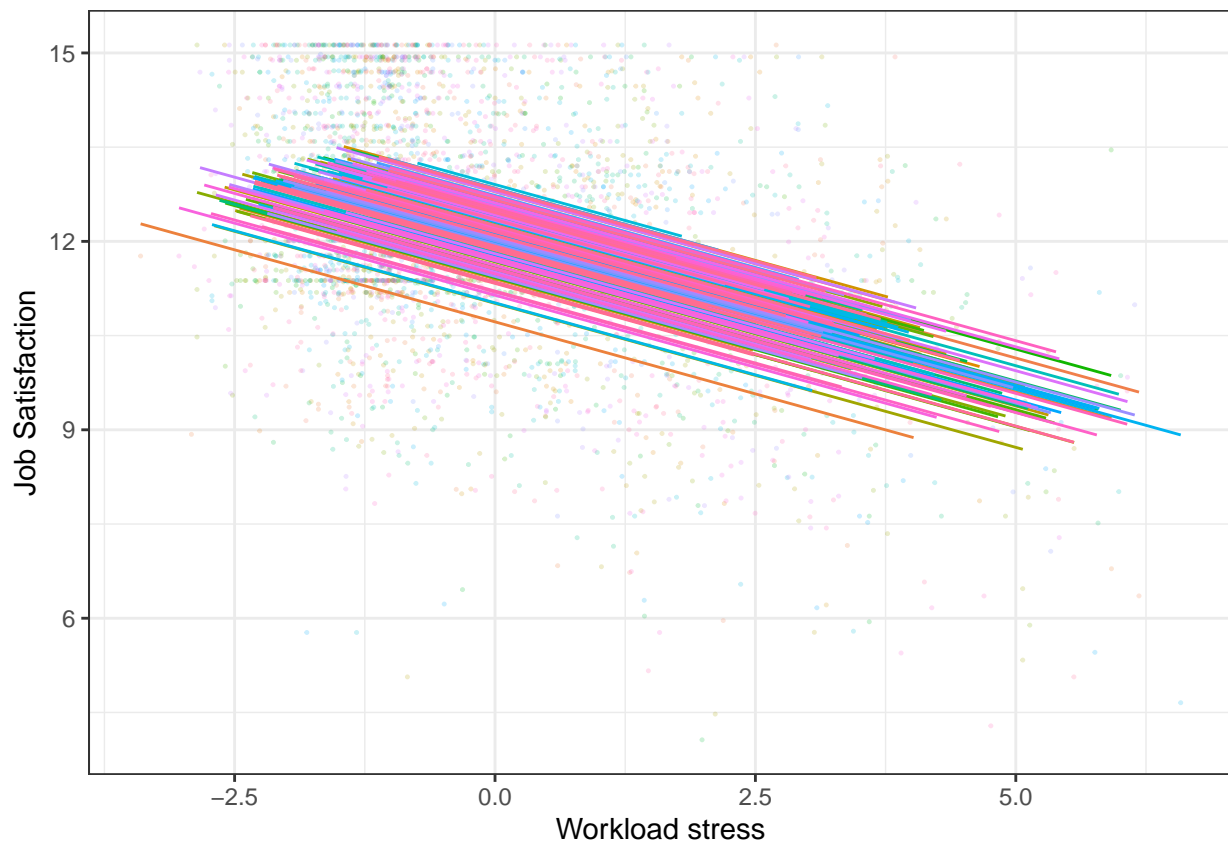
```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



```
# Two separate graphs
p1
```

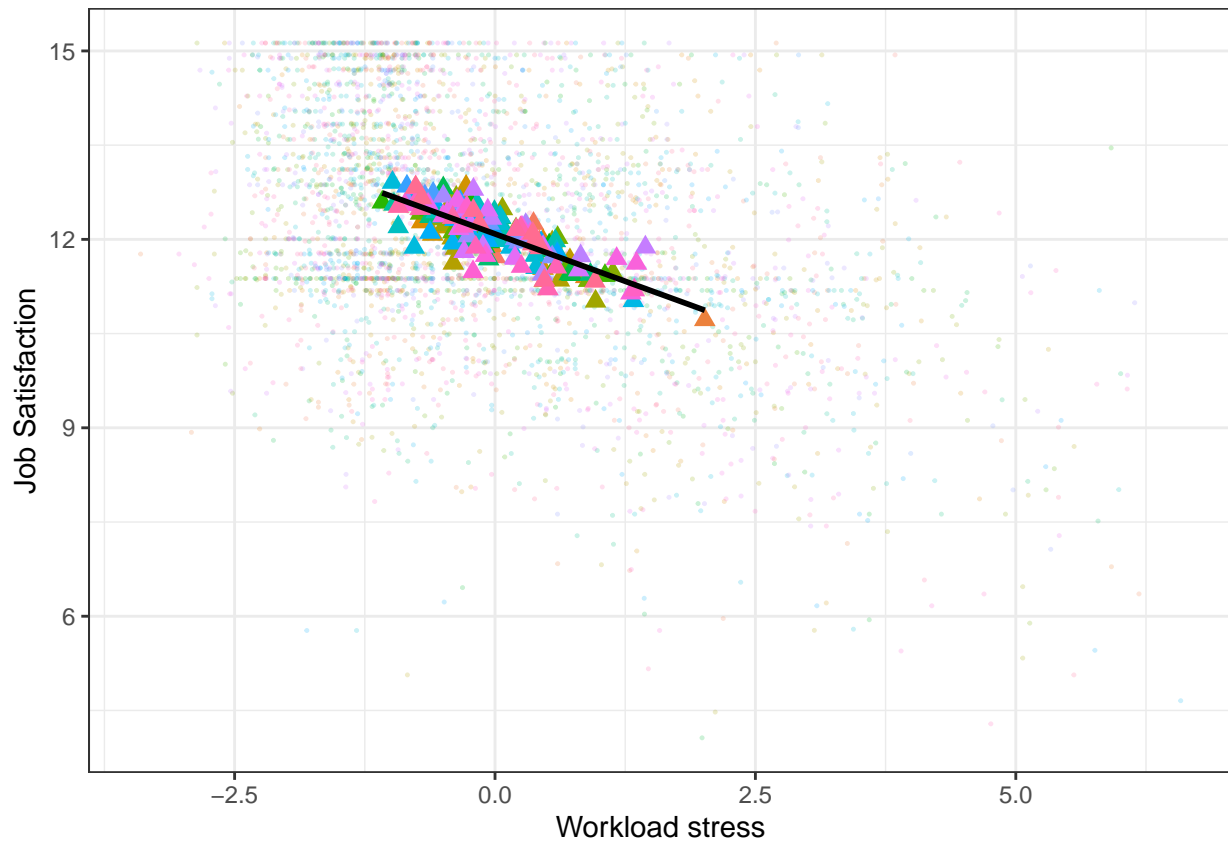
```
## `geom_smooth()` using formula 'y ~ x'
```





p2

```
## `geom_smooth()` using formula 'y ~ x'
```



```
# * How much variance explained? -----
# School-level variance
round((1-(0.1342/0.217)),2)

## [1] 0.38

# Teacher-level variance
round((1-(2.6055/3.218)),2)

## [1] 0.19

# * LRT for school-level variance -----
# Null single level model
fit <- lm(T3JOBBSA ~ T3WELS + T3WELS_CM_GMC, data = df4)
# Likelihood ratio
(ll_simple<-logLik(fit)[1])

## [1] -6531.295

(ll_complex <-logLik(model2)[1])

## [1] -6515.607

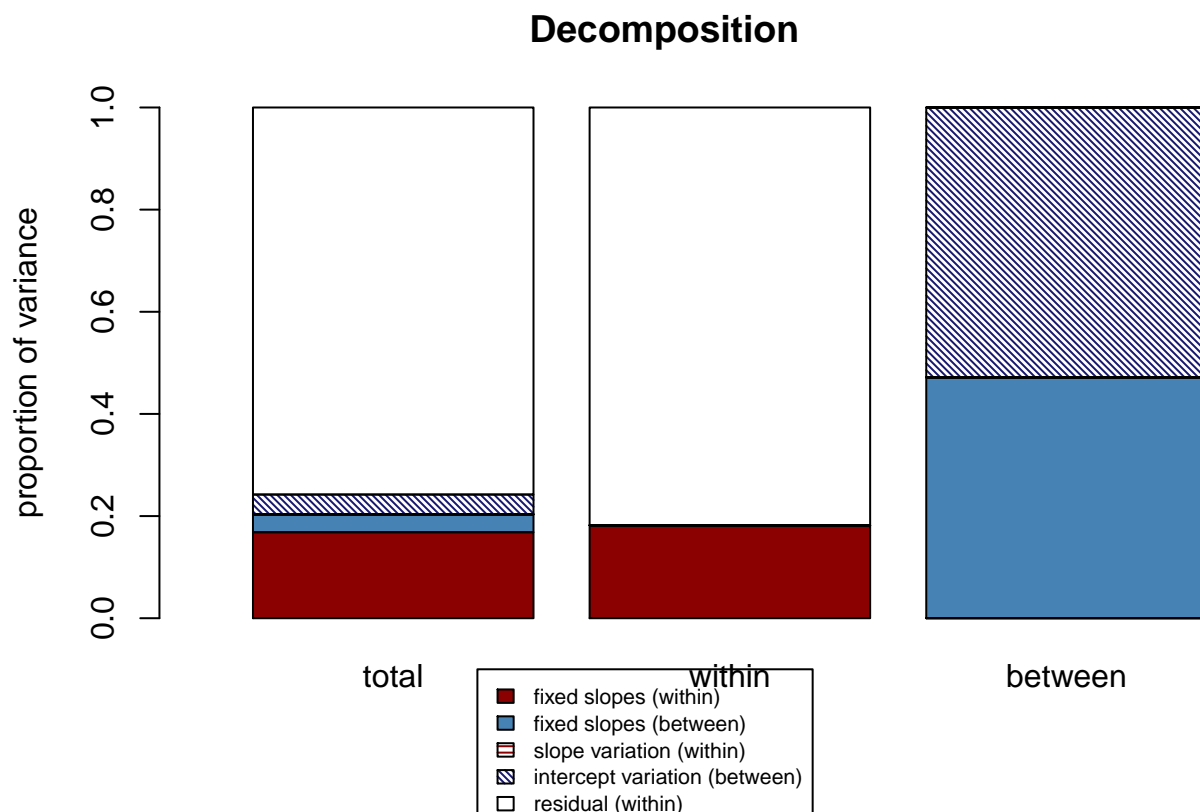
(LR <- -2*ll_simple-(-2*ll_complex)) # 1df because only 1 parameter difference

## [1] 31.37435

(pval_lr <- (pchisq(LR, df=1, lower.tail = FALSE)/2))

## [1] 1.063867e-08
```

```
# * Proportion of variance explained -----
## Use Rights & Sterba (2019)
r2mlm::r2mlm(model2)
```

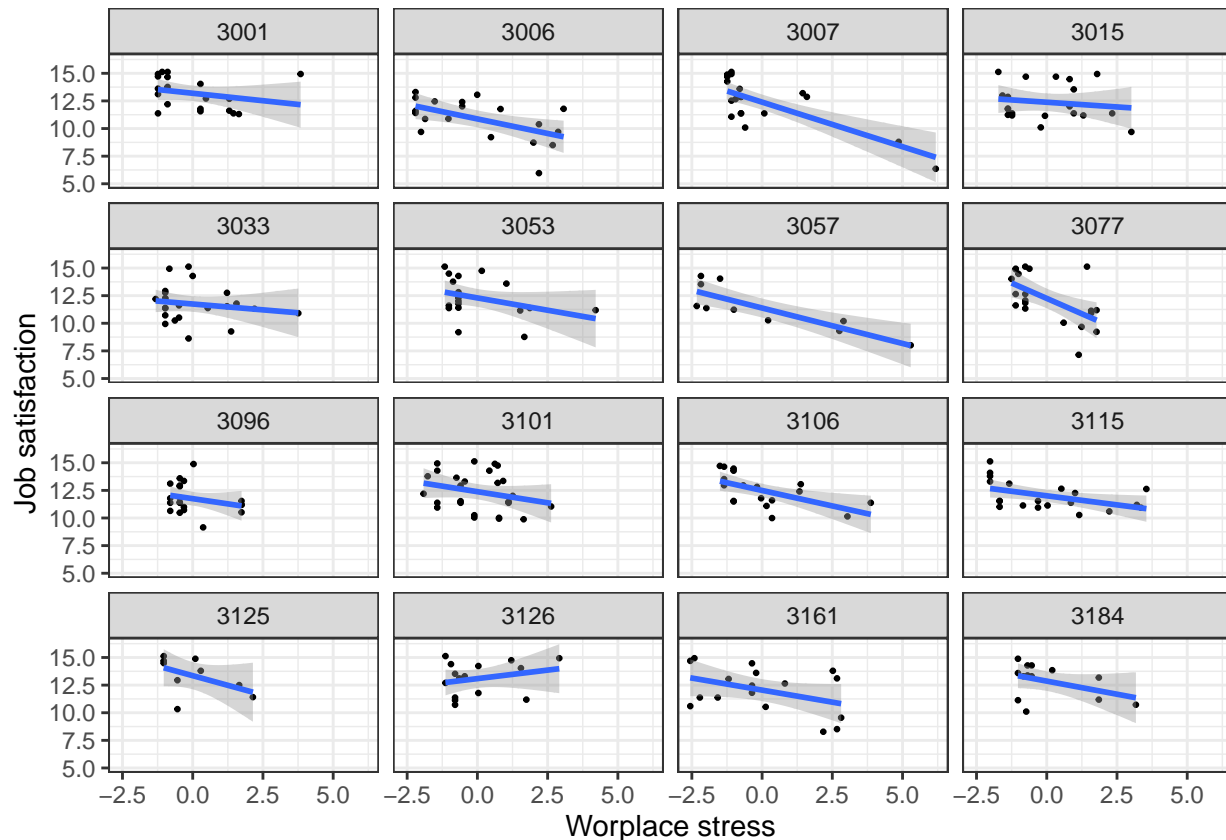


```
## $Decompositions
##          total          within          between
## fixed, within 0.168335407006222 0.181754683645787 NA
## fixed, between 0.0348042999926375 NA 0.471399815696785
## slope variation 0 0 NA
## mean variation 0.0390275065412548 NA 0.528600184303215
## sigma2 0.757832786459886 0.818245316354213 NA
##
## $R2s
##          total          within          between
## f1 0.168335407006222 0.181754683645787 NA
## f2 0.0348042999926375 NA 0.471399815696785
## v 0 0 NA
## m 0.0390275065412548 NA 0.528600184303215
## f 0.20313970699886 NA NA
## fv 0.20313970699886 0.181754683645787 NA
## fvm 0.242167213540114 NA NA
```

```
# Random coefficients model -----
# Graphically explore slopes of a sample
set.seed(2022)
df4 %>%
  # randomly sample 16 schools
  filter(IDSCHOOL %in% sample(unique(IDSCHOOL), 16)) %>%
  ggplot(aes(x = T3WELS_CMC, y = T3JOBSA)) +
```

```
geom_point(size = 0.5) +
geom_smooth(method = "lm") +
facet_wrap(~IDSCHOOL) +
labs(x="Workplace stress",
     y="Job satisfaction")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



```
# Model 3
model3 <- lmer(T3JOBSA ~ T3WELS_CM_GMC + T3WELS_CMC + (1 + T3WELS_CMC | IDSCHOOL),
               data = df4,
               control = lmerControl(optimizer = "bobyqa"))
# Summarize results
summary(model3)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: T3JOBSA ~ T3WELS_CM_GMC + T3WELS_CMC + (1 + T3WELS_CMC | IDSCHOOL)
## Data: df4
## Control: lmerControl(optimizer = "bobyqa")
##
## REML criterion at convergence: 13025.5
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -4.3863 -0.6838 -0.0072  0.7276  3.3600
##
## Random effects:
```

```

## Groups Name Variance Std.Dev. Corr
## IDSCHOOL (Intercept) 0.134613 0.36690
## T3WELS_CMC 0.003715 0.06095 0.92
## Residual 2.594878 1.61086
## Number of obs: 3398, groups: IDSCHOOL, 186
##
## Fixed effects:
## Estimate Std. Error t value
## (Intercept) 12.09370 0.03875 312.13
## T3WELS_CM_GMC -0.62521 0.06730 -9.29
## T3WELS_CMC -0.45534 0.01736 -26.24
##
## Correlation of Fixed Effects:
## (Intr) T3WELS_CM_
## T3WELS_CM_G 0.009
## T3WELS_CMC 0.169 0.052
# Likelihood-based confidence intervals for fixed effects
confint(model3)

## Computing profile confidence intervals ...

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): unexpected decrease in
## profile: using minstep

## Warning in FUN(X[[i]], ...): non-monotonic profile for .sig01

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

```











```

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in nextpar(mat, cc, i, delta, lowcut, upcut): Last two rows have
## identical or NA .zeta values: using minstep

## Warning in FUN(X[[i]], ...): non-monotonic profile for .sig02

## Warning in confint.thpr(pp, level = level, zeta = zeta): bad spline fit
## for .sig01: falling back to linear interpolation

## Warning in confint.thpr(pp, level = level, zeta = zeta): bad spline fit
## for .sig02: falling back to linear interpolation

## Warning in regularize.values(x, y, ties, missing(ties), na.rm = na.rm):
## collapsing to unique 'x' values

##           2.5 %      97.5 %
## .sig01      0.28652790 0.4434053
## .sig02      0.11522518 1.0000000
## .sig03      0.01032606 0.1224459
## .sigma      1.57143308 1.6313482
## (Intercept) 12.01783013 12.1697194
## T3WELS_CM_GMC -0.75799081 -0.4925897
## T3WELS_CMC   -0.48935498 -0.4209101

# * LRT Random effects -----
anova(model2, model3)

## refitting model(s) with ML (instead of REML)

## Data: df4
## Models:

```

```
## model2: T3JOBSA ~ T3WELS_CMC + T3WELS_CM_GMC + (1 | IDSCHOOL)
## model3: T3JOBSA ~ T3WELS_CM_GMC + T3WELS_CMC + (1 + T3WELS_CMC | IDSCHOOL)
##      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model2     5 13027 13057 -6508.3    13017
## model3     7 13025 13068 -6505.5    13011 5.6673  2    0.0588 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# * Variance-covariance matrix -----
VarCorr(model3)$IDSCHOOL
```

```
##              (Intercept) T3WELS_CMC
## (Intercept)  0.13461345 0.02063522
## T3WELS_CMC   0.02063522 0.00371502
## attr("stddev")
## (Intercept)  T3WELS_CMC
##  0.36689706  0.06095096
## attr("correlation")
##              (Intercept) T3WELS_CMC
## (Intercept)  1.0000000  0.9227503
## T3WELS_CMC   0.9227503  1.0000000
```

```
# Plot of schools slopes vs schools intercepts
(myrandomomeff <- ranef(model3, condVar = TRUE))
```

```
## $IDSCHOOL
##      (Intercept)      T3WELS_CMC
## 3001  0.409844586  0.0637460620
## 3002 -0.375977193 -0.0578190353
## 3003  0.136298050  0.0211553061
## 3004  0.392384888  0.0604185635
## 3005 -0.173580200 -0.0237142271
## 3006 -0.460765331 -0.0706396987
## 3007 -0.153789316 -0.0291079574
## 3008  0.168956725  0.0246972689
## 3009  0.056984796  0.0190549736
## 3010 -0.233282051 -0.0364513879
## 3011 -0.012897625 -0.0002068569
## 3012 -0.103213004 -0.0133029591
## 3014  0.157025703  0.0235563127
## 3015  0.183264902  0.0302369217
## 3016  0.003919042  0.0020325817
## 3017 -0.160032906 -0.0247783506
## 3018 -0.267671394 -0.0416947615
## 3019  0.025556065  0.0088925867
## 3020  0.052807502  0.0087790737
## 3021  0.103144405  0.0174387903
## 3022 -0.364142282 -0.0544992848
## 3023  0.622603441  0.0976796401
## 3024 -0.267189197 -0.0405463408
## 3025 -0.014573658 -0.0048527837
## 3026  0.019089572  0.0033997157
## 3027  0.282441300  0.0433157914
## 3028  0.362402506  0.0549109260
## 3029 -0.113759270 -0.0122089253
## 3030 -0.007145036 -0.0026856534
```

```

## 3031 0.001777426 0.0005836431
## 3032 0.075543842 0.0135979888
## 3033 -0.291428116 -0.0423950647
## 3034 -0.765634676 -0.1193790324
## 3035 -0.412830450 -0.0660824088
## 3036 -0.516504596 -0.0812671051
## 3037 0.219278479 0.0322245955
## 3038 0.233015783 0.0373264286
## 3039 -0.194760522 -0.0317106617
## 3040 -0.530610510 -0.0837605876
## 3041 0.076959827 0.0112181447
## 3042 0.420803011 0.0637322692
## 3043 0.357758144 0.0554890100
## 3044 -0.080424175 -0.0112132556
## 3045 -0.164016140 -0.0261466344
## 3046 0.116660845 0.0201987979
## 3047 0.140664949 0.0189088679
## 3048 0.018298504 0.0030265208
## 3050 -0.201994996 -0.0311738588
## 3051 0.261603711 0.0377120261
## 3052 0.195486746 0.0311315791
## 3053 -0.117840859 -0.0178513629
## 3054 -0.080131972 -0.0106722336
## 3055 -0.259264265 -0.0411446325
## 3056 -0.130339552 -0.0201552929
## 3057 -0.171008061 -0.0284409262
## 3058 0.130333822 0.0277696903
## 3059 0.053358303 0.0114102557
## 3060 -0.176238840 -0.0272858973
## 3061 0.402627833 0.0644880997
## 3062 0.125494459 0.0187080141
## 3063 -0.317779438 -0.0496895818
## 3064 -0.321610272 -0.0518584241
## 3065 -0.118552455 -0.0155963105
## 3066 -0.172036690 -0.0246060363
## 3067 -0.144379526 -0.0191742824
## 3068 -0.110088519 -0.0164424686
## 3069 0.429372560 0.0664186756
## 3070 0.230325957 0.0367240262
## 3071 0.138798897 0.0205726367
## 3072 0.092635764 0.0125420233
## 3073 -0.029051620 -0.0053774275
## 3074 -0.419070554 -0.0627182737
## 3075 0.007538616 -0.0009837932
## 3076 -0.055129008 -0.0067285356
## 3077 -0.185807719 -0.0321150252
## 3078 0.251848317 0.0367376814
## 3079 -0.260968627 -0.0372279595
## 3080 -0.037262188 -0.0072384087
## 3081 0.114271046 0.0200543354
## 3083 0.259439361 0.0388681756
## 3084 0.322268537 0.0492789186
## 3085 0.122552520 0.0175686814
## 3086 -0.147611009 -0.0232136003

```

```

## 3087 -0.228532097 -0.0312475127
## 3088 0.150527339 0.0234739635
## 3089 0.075028637 0.0092141136
## 3090 0.071777238 0.0107181487
## 3091 0.390483419 0.0622426236
## 3092 0.251553957 0.0391642420
## 3093 -0.044780024 -0.0086647418
## 3094 0.031582220 0.0031340348
## 3095 0.406249925 0.0645517149
## 3096 -0.460892671 -0.0701245466
## 3097 -0.094600370 -0.0141257901
## 3098 -0.037613411 -0.0119370617
## 3099 -0.064283184 -0.0075776113
## 3100 0.319955720 0.0502903338
## 3101 0.182409664 0.0281391412
## 3102 -0.102256703 -0.0173606713
## 3103 -0.355418153 -0.0578126419
## 3104 0.231969529 0.0370611594
## 3105 -0.679450809 -0.1027590545
## 3106 0.060002887 0.0082255264
## 3107 -0.093575897 -0.0126589218
## 3108 -0.296193136 -0.0475054698
## 3109 0.254158947 0.0418001228
## 3110 0.188272653 0.0299711271
## 3111 0.011988517 0.0005839491
## 3112 0.195311203 0.0331147666
## 3113 -0.525169798 -0.0864040339
## 3114 -0.022868831 -0.0001729091
## 3115 0.079733295 0.0139054807
## 3116 -0.058547273 -0.0109475477
## 3117 -0.360532875 -0.0547247536
## 3118 -0.170340737 -0.0270877070
## 3119 -0.053954706 -0.0108821262
## 3120 0.137218297 0.0216250037
## 3121 0.171446578 0.0266438916
## 3122 -0.115020132 -0.0257130125
## 3123 -0.020362759 -0.0051312106
## 3124 0.261353262 0.0377790440
## 3125 0.216052740 0.0324651591
## 3126 0.342082888 0.0557509203
## 3128 0.163497566 0.0242102384
## 3129 0.012180298 -0.0020144615
## 3130 0.164808313 0.0272463029
## 3131 0.048617683 0.0081416111
## 3132 0.021956881 0.0045042416
## 3133 -0.082236571 -0.0152278437
## 3134 0.244998355 0.0360125149
## 3135 0.079552461 0.0099239929
## 3136 -0.112389195 -0.0126534605
## 3137 -0.010980939 -0.0016224731
## 3138 0.249199121 0.0367470589
## 3139 -0.318716073 -0.0461675897
## 3140 0.319844426 0.0489055937
## 3141 -0.268443365 -0.0412061357

```

```

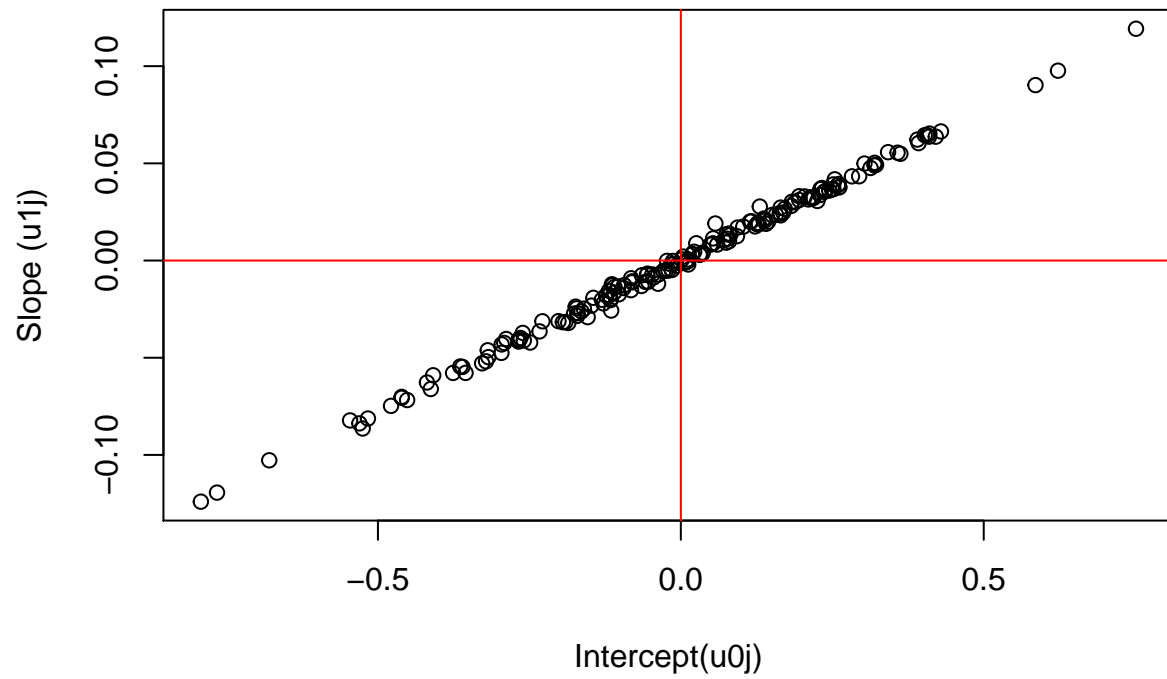
## 3142  0.128747934  0.0186155523
## 3143  0.213849358  0.0325345989
## 3144  0.751367296  0.1192508419
## 3145  0.585402335  0.0902456393
## 3146 -0.264765593 -0.0398254249
## 3147  0.163729661  0.0244994257
## 3148 -0.115761960 -0.0197449426
## 3149 -0.408819159 -0.0590172982
## 3150 -0.065032582 -0.0130782292
## 3151  0.294372162  0.0433636040
## 3152  0.035012171  0.0035123957
## 3153 -0.328087832 -0.0528710303
## 3154  0.093799992  0.0169714917
## 3155 -0.123356894 -0.0179661569
## 3156  0.031026695  0.0029599737
## 3157  0.225403555  0.0306550628
## 3158 -0.016222218 -0.0019601065
## 3159  0.164899708  0.0232650817
## 3160  0.229984318  0.0337120686
## 3161  0.313148864  0.0476261112
## 3162 -0.082136074 -0.0091020137
## 3163  0.410221529  0.0653246580
## 3164 -0.451757560 -0.0717607983
## 3165 -0.127832513 -0.0220602478
## 3166 -0.792336991 -0.1240430974
## 3167  0.236511487  0.0353848591
## 3169 -0.055721987 -0.0073993490
## 3170 -0.288280209 -0.0403632747
## 3171 -0.116073623 -0.0203507867
## 3172  0.204653604  0.0329843955
## 3173  0.239542500  0.0358633830
## 3174 -0.295758824 -0.0431426136
## 3175 -0.248746720 -0.0421668986
## 3176 -0.546040435 -0.0822408988
## 3177  0.216224897  0.0318770682
## 3178 -0.047150001 -0.0071543114
## 3179 -0.024946947 -0.0052092999
## 3180 -0.190585422 -0.0316139676
## 3181  0.144026917  0.0199557075
## 3182 -0.478427985 -0.0747709766
## 3183  0.303099944  0.0499078603
## 3184  0.127599283  0.0193757085
## 3185  0.052871937  0.0087343582
## 3186  0.081490723  0.0131224987
## 3187  0.210611654  0.0314409550
## 3189  0.260575037  0.0393661413
## 3190  0.036188041  0.0040890717
## 3191  0.011285310 -0.0004598365
## 3192 -0.109506619 -0.0136019822
##
## with conditional variances for "IDSCHOOL"
plot(myrandomeff[[1]],
     xlab = "Intercept(u0j)",

```

```

ylab = "Slope (u1j)"
abline(h = 0 , col = "red")
abline(v=0, col = 'red')

```

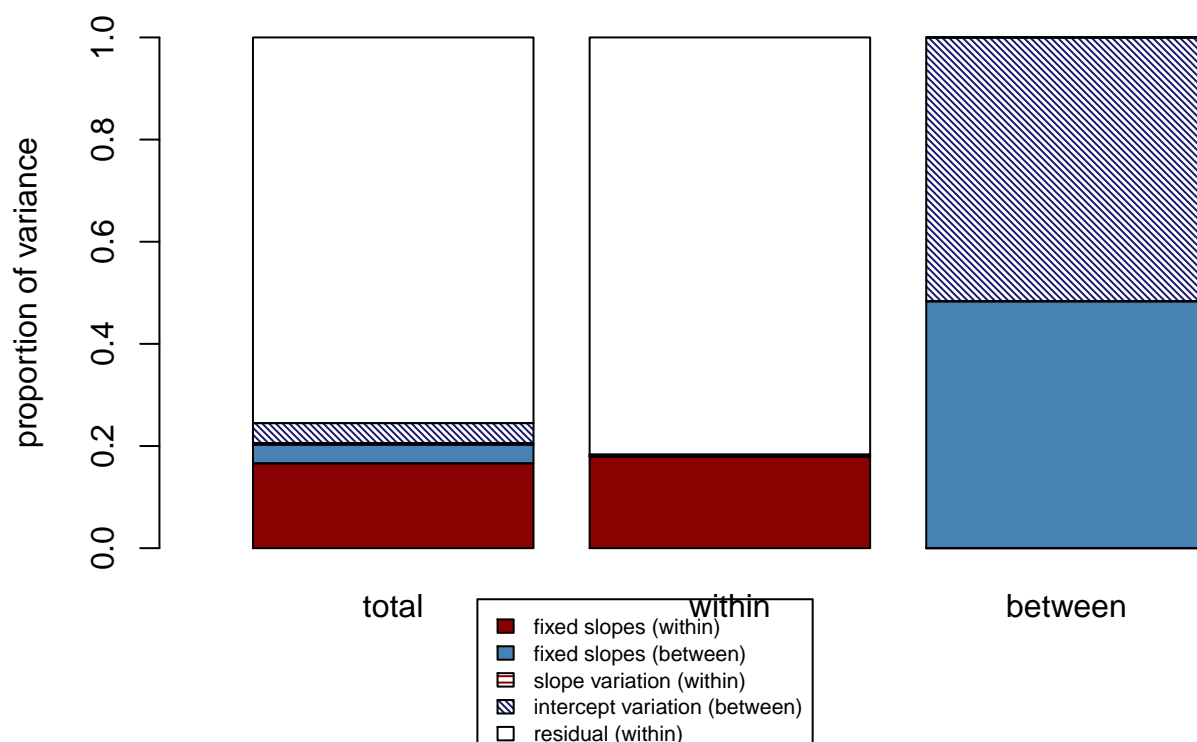


```

# * Proportion of variance explained -----
## Use Rights & Sterba (2019)
r2mlm: r2mlm(model3)

```

## Decomposition

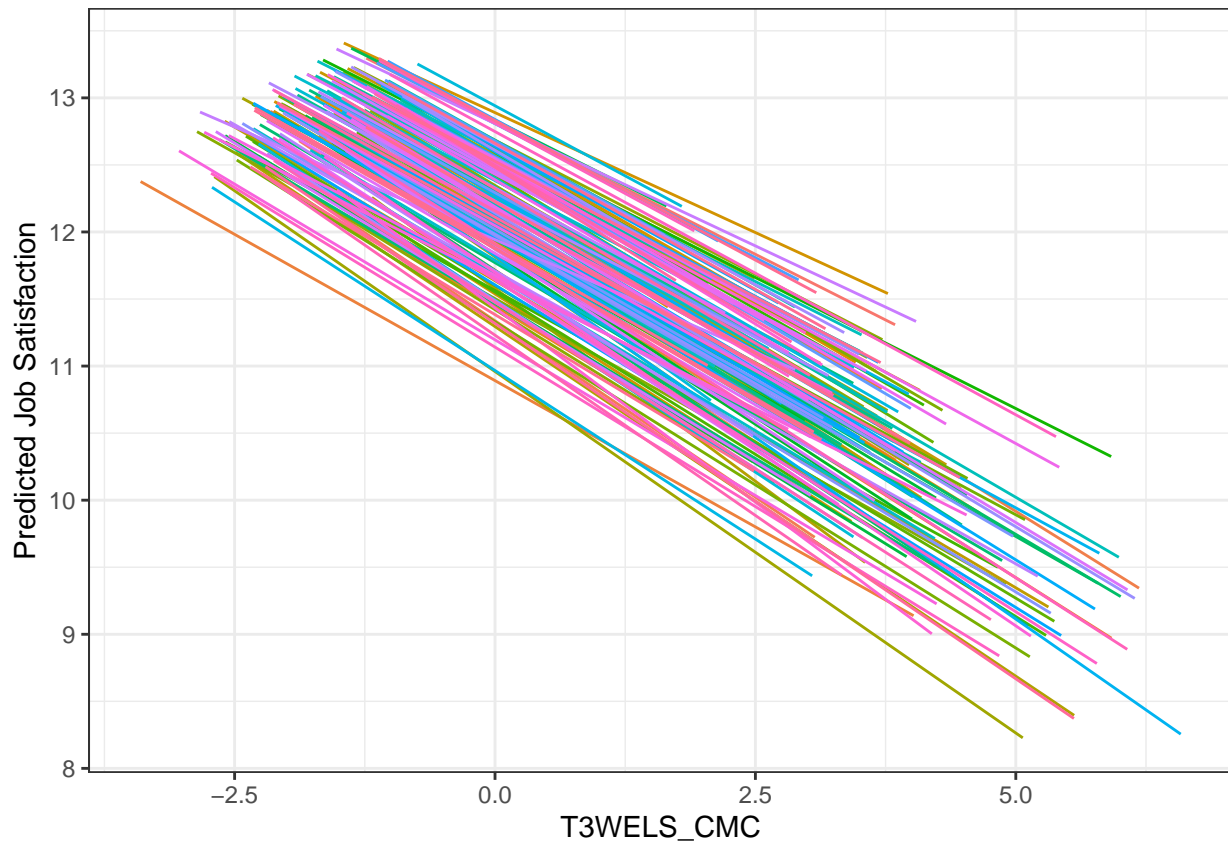


```
## $Decompositions
##          total          within          between
## fixed, within 0.166012446271133 0.179639394811518 NA
## fixed, between 0.0366823322642797 NA 0.483570621016243
## slope variation 0.00297460464010367 0.00321877178099671 NA
## mean variation 0.0391749069269481 NA 0.516429378983757
## sigma2 0.755155709897535 0.817141833407485 NA
##
## $R2s
##          total          within          between
## f1 0.166012446271133 0.179639394811518 NA
## f2 0.0366823322642797 NA 0.483570621016243
## v 0.00297460464010367 0.00321877178099671 NA
## m 0.0391749069269481 NA 0.516429378983757
## f 0.202694778535413 NA NA
## fv 0.205669383175517 0.182858166592515 NA
## fvm 0.244844290102465 NA NA
```

```
# Plotting random slopes
augment(model3, data = df4) %>% # augmented data (adding EB estimates)
  ggplot(aes(x = T3WELS_CMC, y = .fitted, color = factor(IDSCHOOL))) +
  geom_smooth(method = "lm", se = FALSE, size = 0.5) +
  labs(y = "Predicted Job Satisfaction") +
  guides(color = "none")
```

```
## `geom_smooth()` using formula 'y ~ x'
```

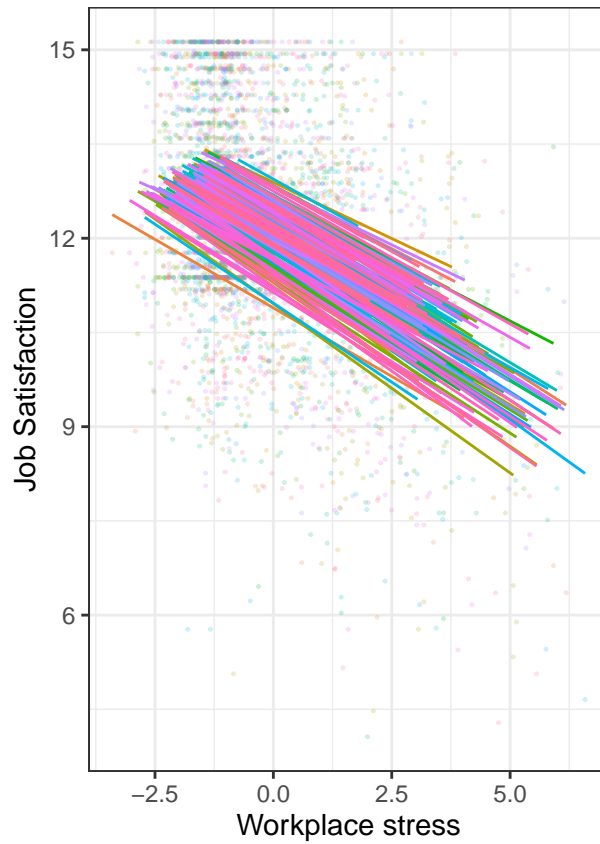




```
# Create a common base graph
pbase <- augment(model3, data = df4) %>%
  ggplot(aes(x = T3WELS_CMC, y = T3JOBBSA, color = factor(IDSCHOOL))) +
  # Add points
  geom_point(size = 0.2, alpha = 0.2) +
  labs(y = "Job Satisfaction") +
  # Suppress legend
  guides(color = "none")
# Lv-1 effect
p1 <- pbase +
  # Add within-cluster lines
  geom_smooth(aes(y = .fitted),
              method = "lm", se = FALSE, size = 0.5) +
  labs(x = "Workplace stress")
# Lv-2 effect
p2 <- pbase +
  # Add group means
  stat_summary(aes(x = T3WELS_CM_GMC, y = .fitted),
               fun = mean,
               geom = "point",
               shape = 17,
               # use triangles
               size = 2.5) +
  # Add between coefficient
  geom_smooth(aes(x = T3WELS_CM_GMC, y = .fitted),
              method = "lm", se = FALSE,
              color = "black") +
```

```
labs(x= "Workplace stress")
# Put the two graphs together (need the gridExtra package)
gridExtra::grid.arrange(p1, p2, ncol = 2)
```

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



```
# Print separate
p1
```

```
## `geom_smooth()` using formula 'y ~ x'
```

