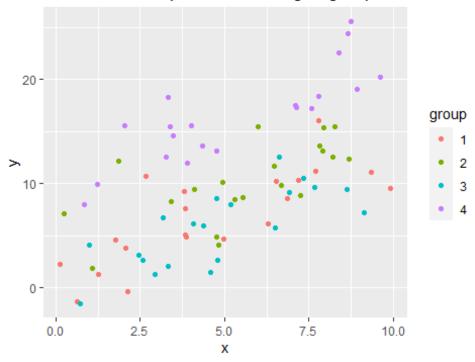
# HW4\_AustinBrewer\_4520

### **Austin Brewer**

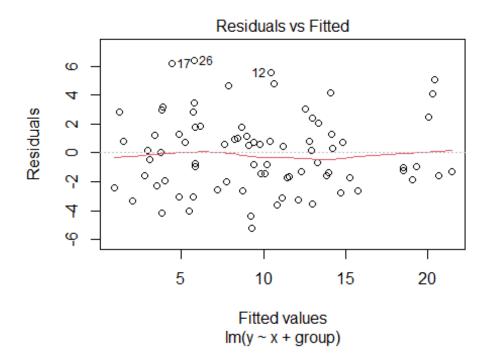
10/30/2023

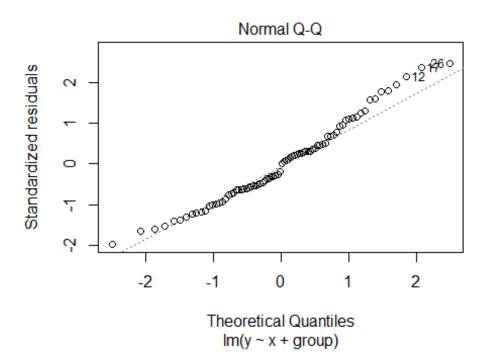
```
#1a
ggplot(dat, aes(x=x, y=y, color=group))+
  geom_point()+
  labs(title="Predictor vs response according to group")
```

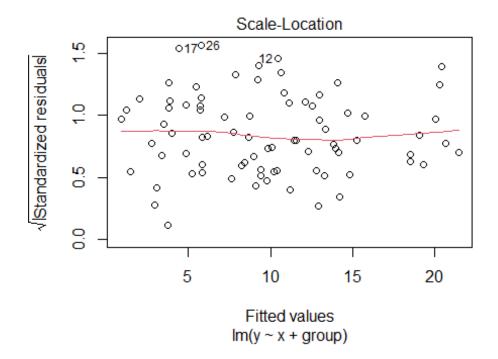
## Predictor vs response according to group

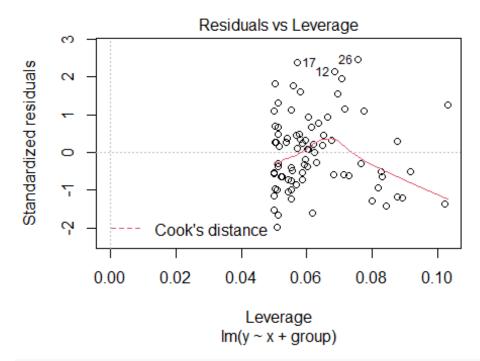


```
#1b
op = options(contrasts = c("contr.sum","contr.poly"))
lmod = lm(y ~ x+group, data=dat)
#summary(lmod)
#Coefficients are as follows: intercept=3.7691, x=1.1804, group1=-2.4687,
group2=-0.1834, group3=-3.716. All are significant except for group 2.
plot(lmod)
```







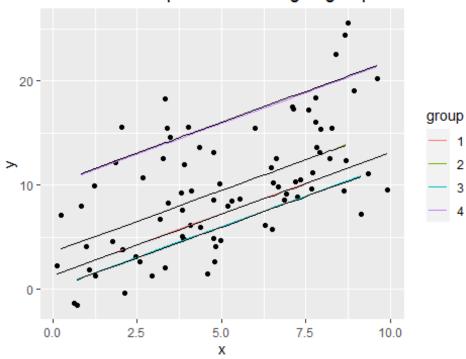


#There don't appear to be major issues with model specifications. The only issues may be some high leverage points but they aren't extreme.

```
#1c
mixmod = lmer(y \sim 1 + x + (1 | group), data = dat)
AIC(lmod)
## [1] 392.836
sumary(mixmod)
## Fixed Effects:
               coef.est coef.se
## (Intercept) 3.75
                        2.32
                        0.12
## x
               1.18
##
## Random Effects:
## Groups
             Name
                         Std.Dev.
## group
             (Intercept) 4.45
## Residual
                         2.70
## ---
## number of obs: 80, groups: group, 4
## AIC = 407.1, DIC = 400.7
## deviance = 399.9
ranef(mixmod)$group
##
     (Intercept)
## 1 -2.4226720
## 2 -0.1812754
## 3 -3.6480247
## 4 6.2519721
#Overall, the two models are very similar. In comparing the fits of the two
models, I looked at AIC for both. The AIC for the fixed model was slightly
lower at 392.8 than the mixed model which was at 407.1. When looking at the
predicted random effects, they are very similar to the predicted fixed
effects (all of them are slightly smaller than their counterpart). The
predicted fixed and random effects are also very close to the true effect
(alpha).
#1d
nullmod = lmer(y \sim 1 + (1|group), data=dat)
KRmodcomp(mixmod, nullmod)
## large : y \sim 1 + x + (1 \mid group)
## small : y \sim 1 + (1 \mid group)
                     ndf
                             ddf F.scaling
##
            stat
                                              p.value
                   1.000 75.062
## Ftest 103.103
                                          1 9.736e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
\#According to the test, the predictor x is a significant inclusion to the
model.
#1e
exactRLRT(mixmod)
##
##
    simulated finite sample distribution of RLRT.
##
    (p-value based on 10000 simulated values)
##
##
## data:
## RLRT = 75.377, p-value < 2.2e-16
#According to the test, the variance of the random effect isn't zero and
therefore the random effect is significant.
#1f
dat2 = cbind(dat, mixmod=predict(mixmod), lmod=predict(lmod))
ggplot(dat2, aes(x=x, y=y))+
  geom_point()+
  geom_line(aes(x,mixmod, color=group))+
  geom_line(aes(x,lmod, group=group))+
  labs(title="Predictor vs response according to group")
```

## Predictor vs response according to group

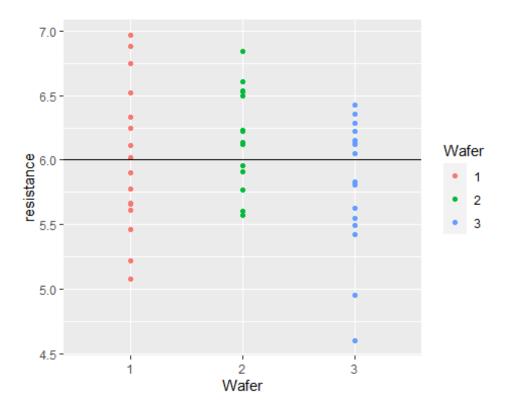


#One major observation is that the two models perform almost identically. I colored the mixed model groups and left the fixed model groups as black. The lines follow identical slopes with very minor intercept differences. This

leads into another major takeaway, which is that all groups have identical slopes. This indicates the slope is measured by pooling the sample together, while the intercepts are capturing all the variation between the groups.

#### #2a

```
ggplot(semicond, aes(x=Wafer, y=resistance, color=Wafer))+
  geom_point()+
  geom_hline(yintercept = (mean(semicond$resistance)))
```



#It seems that the mean for wafer 2 is situated above the overall mean while the wafer 3 mean is situated slightly below. Wafer 2 looks to have the lowest variance, while wafer 1 and 3 appear to have a similar variance. With that being said, the resistance for wafer 1 is evenly distributed, while wafer 3's data is inconsistent and may contain a few high leverage points.

```
#2b
```

```
fixmod = lm(resistance ~ 1+ET+position+(ET*position), data=semicond)
#summary(fixmod)
```

#The only significant predictors in the model are the intercept, ET=1, and position=3 The intercept is set at the mean of 6.0029.

#### #2c

```
mmod = lmer(resistance ~ 1+ET+position+(ET*position)+(1|Grp), data=semicond)
#sumary(mmod)
```

#The standard deviation of the random effect (Grp) in this model is 0.33.

```
#2d
intmod = lmer(resistance ~ 1+position+ET+(1|Grp), data=semicond)
KRmodcomp(mmod,intmod)
## large : resistance ~ 1 + ET + position + (ET * position) + (1 | Grp)
## small : resistance ~ 1 + position + ET + (1 | Grp)
##
            stat
                     ndf
                             ddf F.scaling p.value
## Ftest 0.8092 9.0000 24.0000
                                         1 0.6125
#P-val of 0.6, so the interaction can be removed.
ETmod = lmer(resistance ~ 1+position+(1|Grp), data=semicond)
KRmodcomp(intmod,ETmod)
## large : resistance ~ 1 + position + ET + (1 | Grp)
## small : resistance ~ 1 + position + (1 | Grp)
##
                   ndf
                         ddf F.scaling p.value
           stat
## Ftest 1.9415 3.0000 8.0000
                                      1 0.2015
#P-val of 0.2015, so ET can be removed.
Posmod = lmer(resistance ~ 1+(1|Grp), data=semicond)
KRmodcomp(ETmod, Posmod)
## large : resistance ~ 1 + position + (1 | Grp)
## small : resistance \sim 1 + (1 \mid Grp)
                            ddf F.scaling p.value
##
                     ndf
            stat
## Ftest 3.5714 3.0000 33.0000
                                         1 0.02427 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#P-val of 0.0243, so position should be left in the model.
#2e
exactRLRT(ETmod)
##
## simulated finite sample distribution of RLRT.
##
## (p-value based on 10000 simulated values)
##
## data:
## RLRT = 17.095, p-value < 2.2e-16
#With a P-val of 0, the random effect should be left in the model. That means
the final model includes the intercept, position, and Grp (special
interaction between ET and Wafer).
```