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```
library(dplyr)
library(ggplot2)
library(car)
library(ggpubr)
library(tidyverse)
library(rstatix)
library(ggstatsplot)

setwd("C:/Users/Laura/Documents/code/MA-541")
df <- read.csv("Crime_R.csv")
# split data into year 0 and year + 10
dim(df)
```

```
## [1] 47 27
```

```
names(df)
```

```
##  [1] "CrimeRate"           "Youth"               "Southern"           
##  [4] "Education"           "ExpenditureYear0"    "LabourForce"        
##  [7] "Males"               "MoreMales"           "StateSize"          
## [10] "YouthUnemployment"   "MatureUnemployment"  "HighYouthUnemploy"  
## [13] "Wage"                "BelowWage"           "CrimeRate10"        
## [16] "Youth10"             "Education10"         "ExpenditureYear10"  
## [19] "LabourForce10"       "Males10"             "MoreMales10"        
## [22] "StateSize10"         "YouthUnemploy10"     "MatureUnemploy10"   
## [25] "HighYouthUnemploy10" "Wage10"              "BelowWage10"
```

```
head(df,2)
```

```
##   CrimeRate Youth Southern Education ExpenditureYear0 LabourForce Males
## 1      45.5   135        0      12.4               69         540   965
## 2      52.3   140        0      10.9               55         535  1045
##   MoreMales StateSize YouthUnemployment MatureUnemployment HighYouthUnemploy
## 1         0         6                80                 22                 1
## 2         1         6               135                 40                 1
##   Wage BelowWage CrimeRate10 Youth10 Education10 ExpenditureYear10
## 1  564       139        26.5     135        12.5                71
## 2  453       200        35.9     135        10.9                54
##   LabourForce10 Males10 MoreMales10 StateSize10 YouthUnemploy10
## 1           564     974           0           6              82
## 2           540    1039           1           7             138
##   MatureUnemploy10 HighYouthUnemploy10 Wage10 BelowWage10
## 1               20                   1    632         142
## 2               39                   1    521         210
```

```
tail(df,2)
```

```
##    CrimeRate Youth Southern Education ExpenditureYear0 LabourForce Males
## 46     157.7   136        0      15.1              149         577   994
## 47     161.8   131        0      13.2              160         631  1071
##    MoreMales StateSize YouthUnemployment MatureUnemployment HighYouthUnemploy
## 46         0       157               102                 39                 0
## 47         1         3               102                 41                 0
##    Wage BelowWage CrimeRate10 Youth10 Education10 ExpenditureYear10
## 46  673       167       177.2     140        15.2               141
## 47  674       152       178.2     132        13.2               143
##    LabourForce10 Males10 MoreMales10 StateSize10 YouthUnemploy10
## 46           578     995           0         160             110
## 47           632    1058           1           4             100
##    MatureUnemploy10 HighYouthUnemploy10 Wage10 BelowWage10
## 46               40                   0    739         169
## 47               40                   0    748         150
```

```
df0 <- df %>%
  select(-ends_with('10'))
df10 <- df %>%
  select(ends_with('10'))

#str(df)
```

The Crime Rate dataset is comprised of data collected on crime rates and associated variables from two different time periods in the United States. The data is comprised of 27 columns with 47 rows of data. The first 14 columns are the data collected in the first time period. Additionally in the first set of columns is a column called Southern, which is a binary variable denoting whether a state is classified as Southern or not. The final 13 columns are are the same data collected as the first 13 with the exception of being 10 years in the future. The Southern column applys to both time periods of data.

The first question we will examine will be whether there is a relationship between Males and Southern states. To accomplish this we will use 3 columns; Southern, Males, and Males10. To analyze differences we will need to engineer Southern variable that corresponds to Males10. The first group of Males at what we will call time 0 will be code “1” if it is a Southern state and “0” if not. In the second group we will use “4” to denote a Southern state and “3” otherwise. In this way we will have 4 groups of Males. Before we perform our testing we will examine the data in more depth.

The Males and Males10 columns refer to the number of males per 1000 females in the examined state.

First we will look at how the data is comprised using stem and histogram plots.

```
df1 <- df[,c("Southern","Males")]
df2 <- df[,c("Southern","Males10")]
stem(df$Southern)
```

```
##
##   The decimal point is 1 digit(s) to the left of the |
##
##    0 | 0000000000000000000000000000000
##    2 |
##    4 |
##    6 |
##    8 |
##   10 | 0000000000000000
```

```
stem(df$Males)
```

```
##
##   The decimal point is 1 digit(s) to the right of the |
##
##    92 | 48
##    94 | 803356
##    96 | 24445688992223478
##    98 | 1244556690468
##   100 | 228
##   102 | 498
##   104 | 59
##   106 | 1
```

```
stem(df$Males10)
```

```
##
##   The decimal point is 1 digit(s) to the right of the |
##
##    92 | 5
##    94 | 5899269
##    96 | 28890134688
##    98 | 022233377992333359
##   100 | 131
##   102 | 4499
##   104 | 08
##   106 | 9
```

We can see from the stem plots that we have more Southern states. We should note that although it is not explicity stated in the data what constitutes a Southern state the data seems to align with the US census bureau's definition of a Southern state. The US census counts 16 states in total as Southern States, which appears to align with our data. Alternatively we can see there are 31 “0” states which in total make 47 states counted in this dataset. We are not told what comprises the 31 non-Southern states.

```
sum(df$Southern == 1)
```

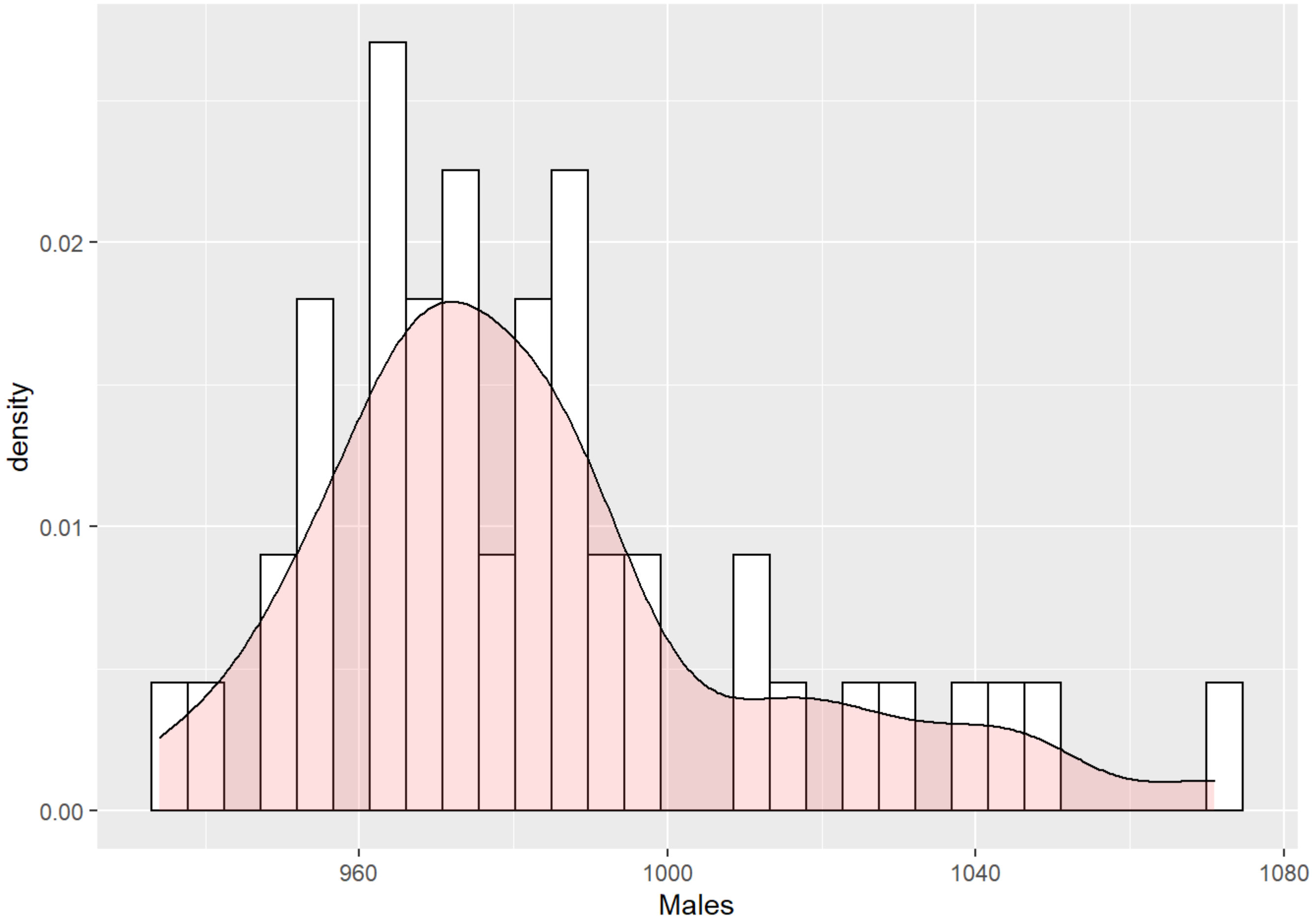
```
## [1] 16
```

```
sum(df$Southern == 0)
```

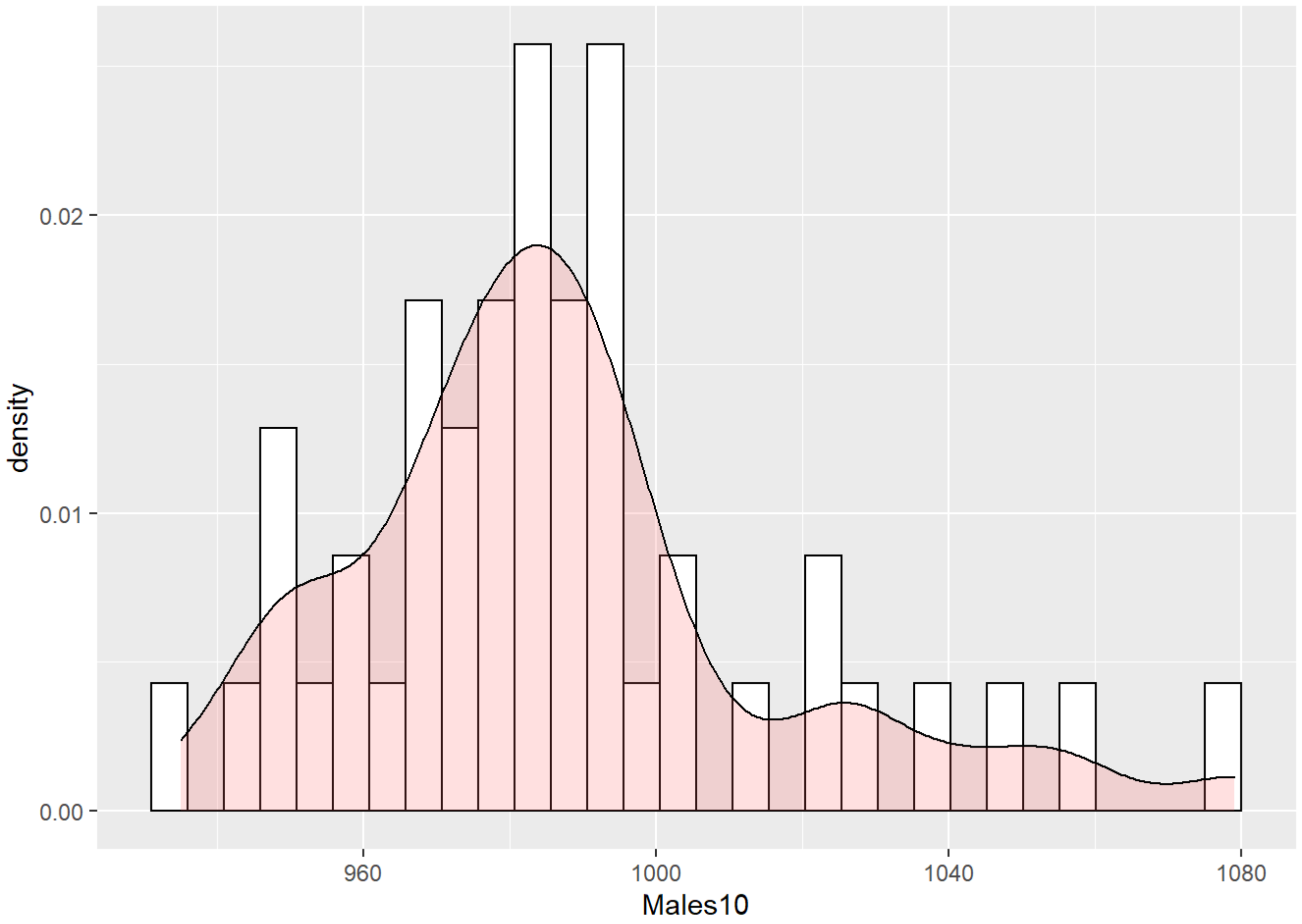
```
## [1] 31
```

From the stem plots we can see that Males and Males10 both appear to be rightly skewed. We can examaine this in more detail using a histogram.

```
ggplot(df, aes(x=Males)) +
 geom_histogram(aes(y=..density..), colour="black", fill="white")+
 geom_density(alpha=.2, fill="#FF6666")
```



```
ggplot(df, aes(x=Males10)) +
 geom_histogram(aes(y=..density..), colour="black", fill="white")+
 geom_density(alpha=.2, fill="#FF6666")
```



More detailed examination with our histograms and density plots again show us that data may be skewed to the right. This will be important to note as we further examine whether there is a difference in means between groups of data.

With this intuition we will examine using anova whether there is a significant difference in group means. To accomplish this we must first encode our variables as previously described and then stack the data frames on top of eachother. Next we will run an anova test on the data. We formulate the null hypothesis that there is no difference in means between the groups of data and the alternative hypothesis that there is a difference of means.

```
df2$Southern <- ifelse(df2$Southern == 0, 3,4)
names(df2)[2] <- "Males"

df_stack <- rbind(df1,df2)
df_stack$Southern <- as.factor(df_stack$Southern)

aov_test <- aov(Males ~ Southern, data=df_stack)
summary(aov_test)
```

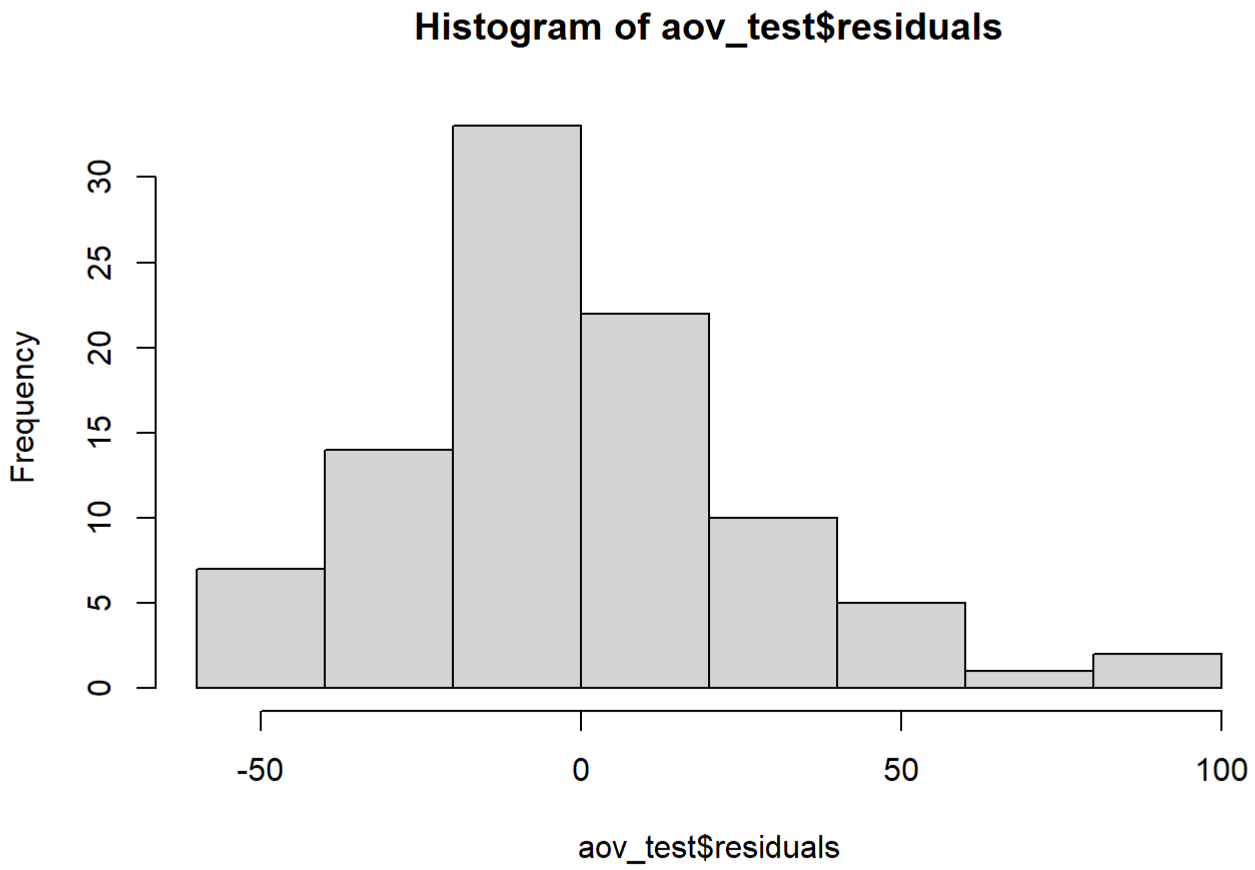
```
##             Df Sum Sq Mean Sq F value Pr(>F)
## Southern     3   8765  2921.8   3.627  0.016 *
## Residuals   90  72501   805.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It appears from the results that we can reject our null hypothesis that the means of the groups are equal.

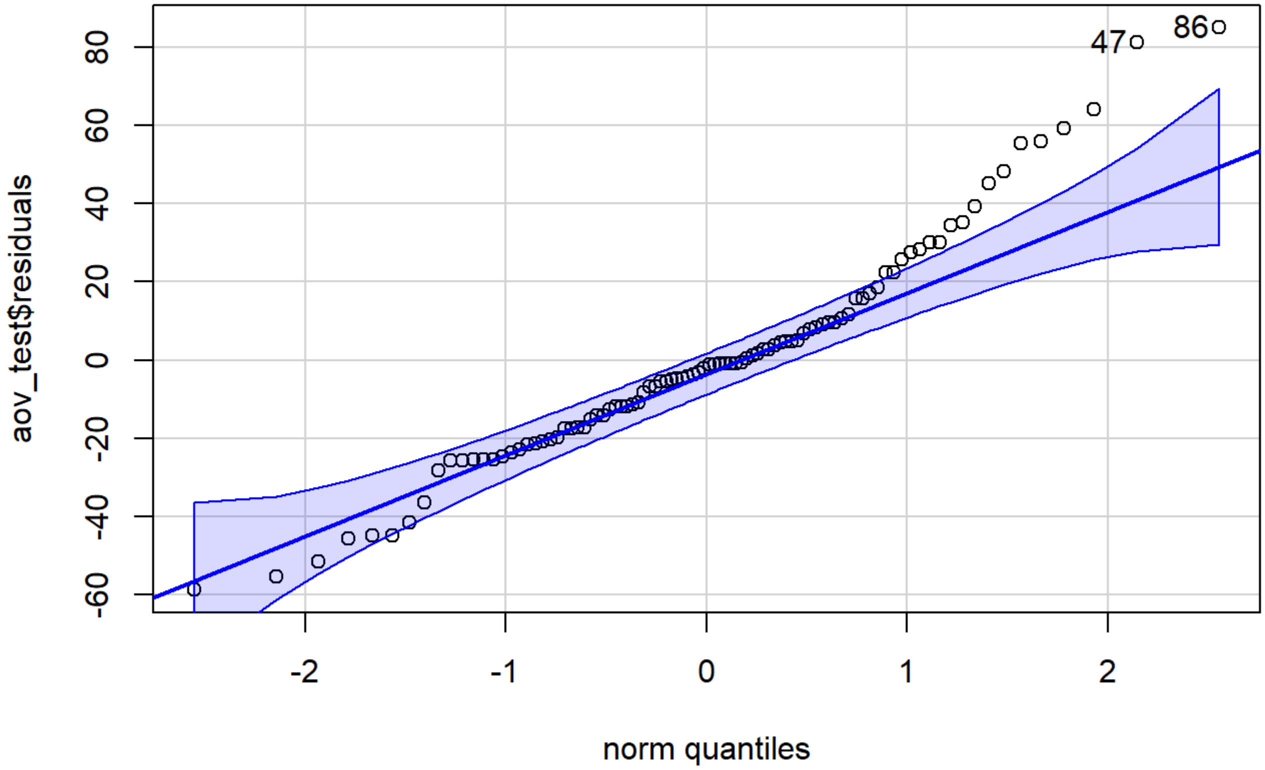
Our next step is to perform post-hoc teting to see which groups are different. First though we would like to examine our results in more detail to see what tests we need to perform.

We examine the residuals of the anova results to see if our data meets the normality assumption needed for tukey or bonferroni. We will do this graphically through a histogram of the residuals and qqplot.

```
hist(aov_test$residuals)
```



```
qqPlot(aov_test$residuals)
```



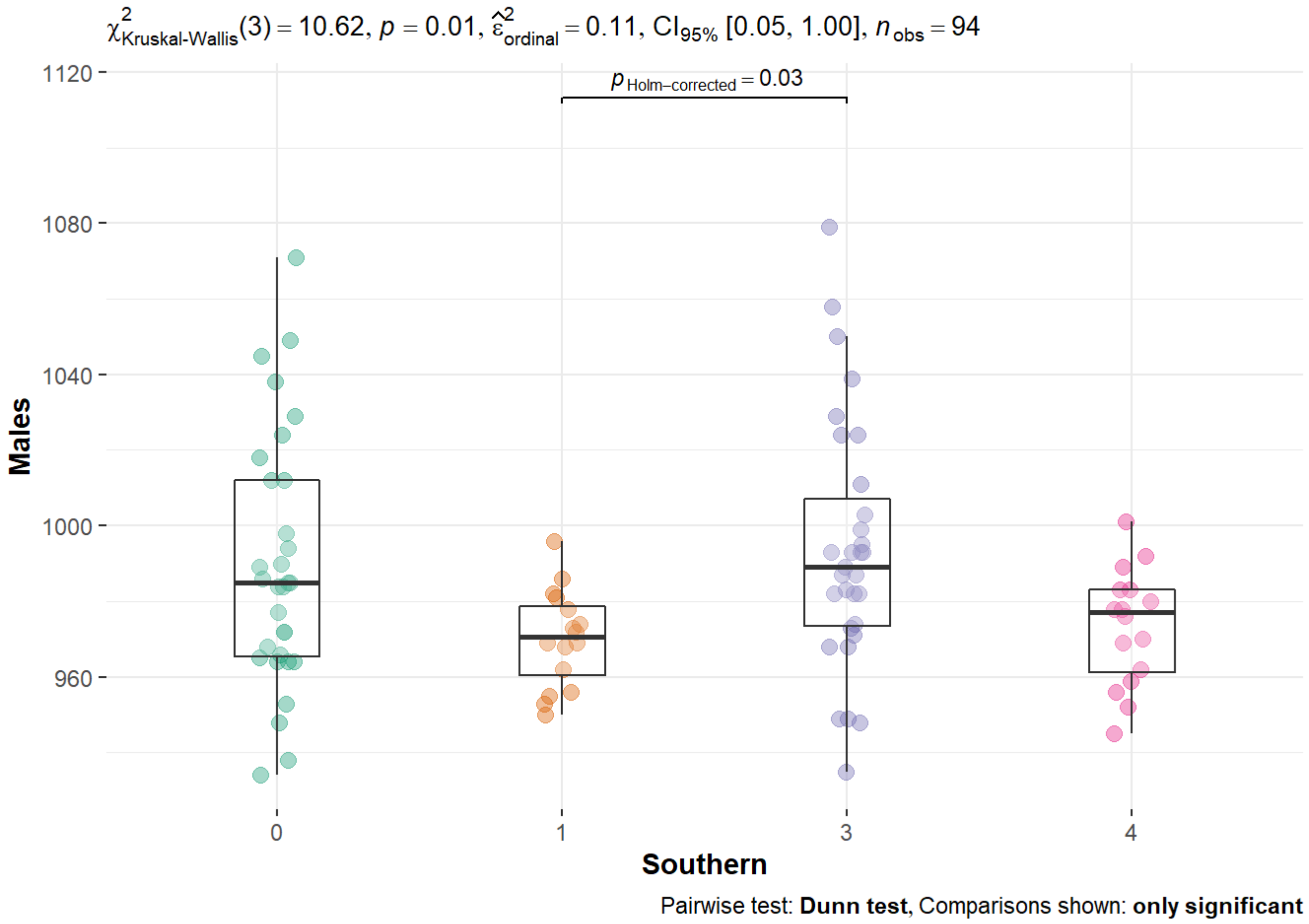
```
## [1] 86 47
```

Graphically it appears that the residuals are not nornally distributed but we need to examine this more formally with a kruskal test

```
kruskal.test(Males ~ Southern, data = df_stack)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Males by Southern
## Kruskal-Wallis chi-squared = 10.624, df = 3, p-value = 0.01394
```

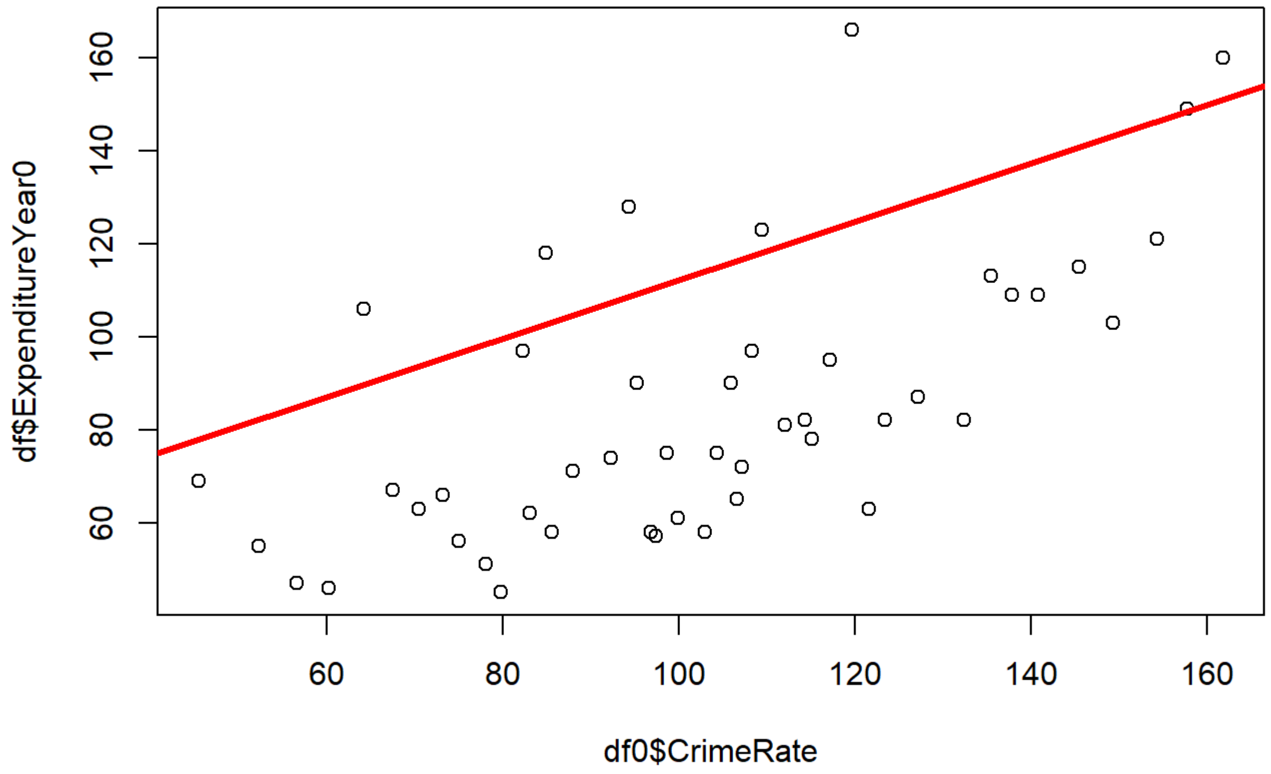
```
ggbetweenstats(
  data = df_stack,
  x = "Southern",
  y = "Males",
  type = "nonparametric", # ANOVA or Kruskal-Wallis
  plot.type = "box",
  pairwise.comparisons = TRUE,
  pairwise.display = "significant",
  centrality.plotting = FALSE,
  bf.message = FALSE
)
```



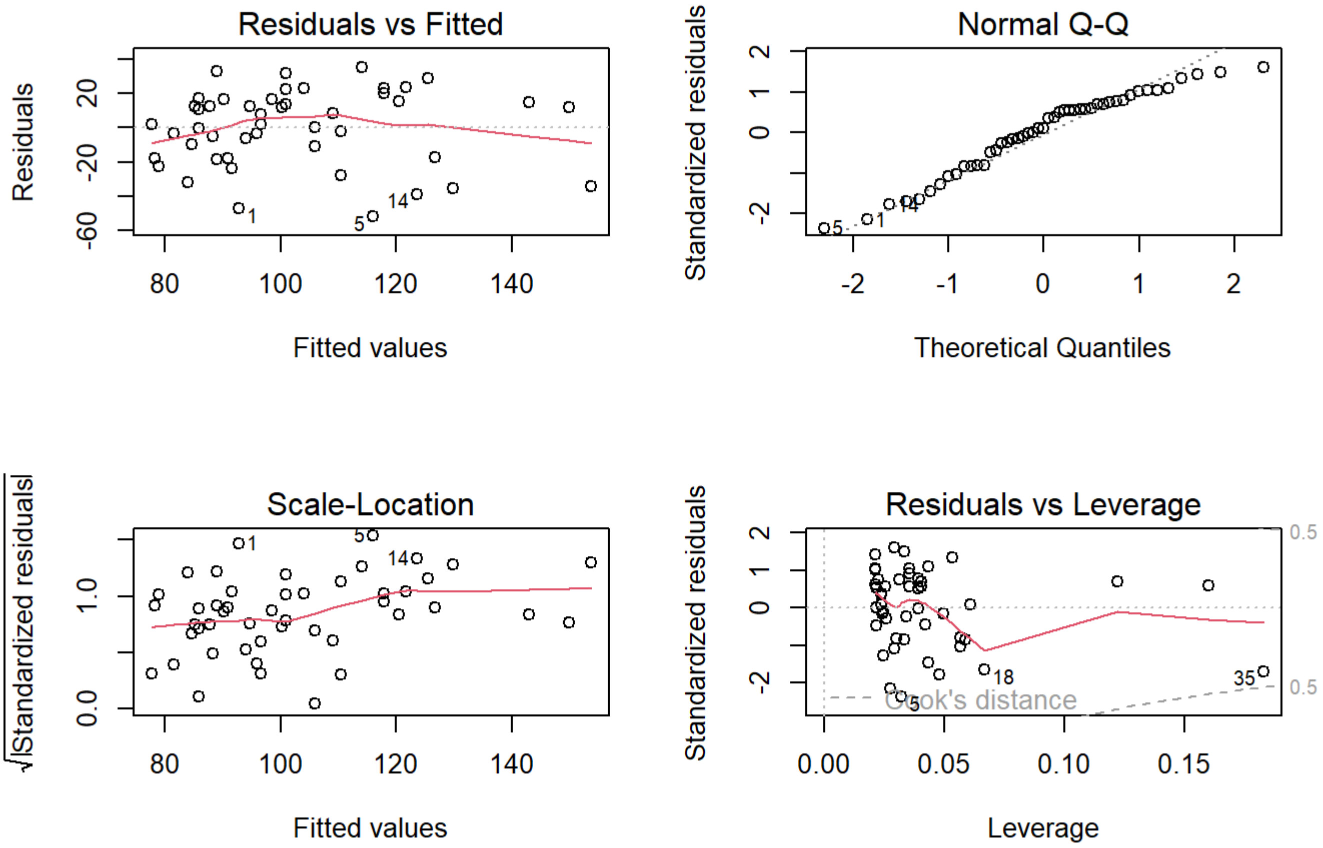
```
lm.fit <- lm(CrimeRate ~ ExpenditureYear0, data=df0)
summary(lm.fit)
```

```
## 
## Call:
## lm(formula = CrimeRate ~ ExpenditureYear0, data = df0)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -51.802 -17.477   2.174  15.728  35.183 
## 
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)    
## (Intercept)       49.4067     9.9479   4.967 1.03e-05 ***
## ExpenditureYear0   0.6283     0.1106   5.680 9.29e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 22.29 on 45 degrees of freedom
## Multiple R-squared:  0.4176, Adjusted R-squared:  0.4046 
## F-statistic: 32.26 on 1 and 45 DF,  p-value: 9.293e-07
```

```
plot(df0$CrimeRate, df$ExpenditureYear0)
abline(lm.fit, lwd=3, col="red")
```



```
par(mfrow = c(2,2))
plot(lm.fit)
```



```
model <- lm(CrimeRate~.,data=df0)
summary(model)
```

```
##
## Call:
## lm(formula = CrimeRate ~ ., data = df0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -33.204 -10.557   2.919  10.391  32.707
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        -258.30363  192.43539  -1.342  0.18866
## Youth                 0.86498    0.35319   2.449  0.01980 *
## Southern              0.56966   12.04365   0.047  0.96256
## Education             6.43119    3.75033   1.715  0.09575 .
## ExpenditureYear0      0.71271    0.20199   3.528  0.00125 **
## LabourForce           0.10771    0.12281   0.877  0.38680
## Males                -0.18383    0.23656  -0.777  0.44265
## MoreMales            17.33920   15.83577   1.095  0.28147
## StateSize            -0.09895    0.11444  -0.865  0.39349
## YouthUnemployment    -0.09173    0.46132  -0.199  0.84361
## MatureUnemployment    0.68776    0.99491   0.691  0.49423
## HighYouthUnemploy    -4.49806   10.82134  -0.416  0.68035
## Wage                  0.19189    0.08950   2.144  0.03950 *
## BelowWage             0.55336    0.20693   2.674  0.01156 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.17 on 33 degrees of freedom
## Multiple R-squared:  0.6842, Adjusted R-squared:  0.5598
## F-statistic:   5.5 on 13 and 33 DF,  p-value: 3.616e-05
```

```
lm.fit <- lm(
  CrimeRate ~
    Education + Youth + Wage + BelowWage
    + ExpenditureYear0, data=df0)

lm.fit2 <- lm(
  CrimeRate ~
    Youth + Wage + BelowWage
    + ExpenditureYear0, data=df0
)

summary(lm.fit)
```

```
## 
## Call:
## lm(formula = CrimeRate ~ Education + Youth + Wage + BelowWage + 
##     ExpenditureYear0, data = df0)
## 
## Residuals:
##    Min     1Q Median     3Q    Max 
## -43.32 -12.69   3.12  10.78  32.52 
## 
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)    
## (Intercept)      -338.74486   90.91882  -3.726 0.000588 ***
## Education           4.72597    3.05412   1.547 0.129450    
## Youth               0.78508    0.29627   2.650 0.011387 *  
## Wage                0.20208    0.08097   2.496 0.016679 *  
## BelowWage           0.55952    0.15831   3.534 0.001029 ** 
## ExpenditureYear0    0.69979    0.15487   4.519  5.2e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 18.55 on 41 degrees of freedom
## Multiple R-squared:  0.6326, Adjusted R-squared:  0.5878 
## F-statistic: 14.12 on 5 and 41 DF,  p-value: 4.872e-08
```

```
summary(lm.fit2)
```

```
## 
## Call:
## lm(formula = CrimeRate ~ Youth + Wage + BelowWage + ExpenditureYear0, 
##     data = df0)
## 
## Residuals:
##    Min     1Q Median     3Q    Max 
## -46.02 -12.06   3.09  12.70  33.83 
## 
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)    
## (Intercept)      -265.89320   79.06065  -3.363 0.001653 ** 
## Youth               0.76376    0.30082   2.539 0.014913 *  
## Wage                0.21169    0.08206   2.580 0.013475 *  
## BelowWage           0.49014    0.15432   3.176 0.002797 ** 
## ExpenditureYear0    0.66540    0.15579   4.271 0.000109 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 18.86 on 42 degrees of freedom
## Multiple R-squared:  0.6111, Adjusted R-squared:  0.5741 
## F-statistic:  16.5 on 4 and 42 DF,  p-value: 3.367e-08
```

```
anova(lm.fit, lm.fit2)
```

```
## Analysis of Variance Table
##
## Model 1: CrimeRate ~ Education + Youth + Wage + BelowWage + ExpenditureYear0
## Model 2: CrimeRate ~ Youth + Wage + BelowWage + ExpenditureYear0
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1     41 14110
## 2     42 14934 -1   -824.05 2.3945 0.1294
```

```
lm.fit3 <- lm(
  CrimeRate ~
    + log10(Youth)
    + log10(Wage)
    + log10(BelowWage)
    + log10(ExpenditureYear0), data=df0
)

lm.fit4 <- lm(
  CrimeRate ~
  + log10(Youth)
  + log10(BelowWage)
  + log10(ExpenditureYear0), data=df0
)

summary(lm.fit3)
```

```
##
## Call:
## lm(formula = CrimeRate ~ +log10(Youth) + log10(Wage) + log10(BelowWage) +
##     log10(ExpenditureYear0), data = df0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.094 -12.065   0.593  12.248  27.813
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -1719.42     364.93  -4.712 2.70e-05 ***
## log10(Youth)              248.00      89.06   2.785 0.008003 **
## log10(Wage)               168.54      75.88   2.221 0.031799 *
## log10(BelowWage)          218.64      56.90   3.843 0.000405 ***
## log10(ExpenditureYear0)   176.39      29.61   5.958 4.57e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.07 on 42 degrees of freedom
## Multiple R-squared:  0.6815, Adjusted R-squared:  0.6512
## F-statistic: 22.47 on 4 and 42 DF,  p-value: 5.63e-10
```

```
summary(lm.fit4)
```

```
##
## Call:
## lm(formula = CrimeRate ~ +log10(Youth) + log10(BelowWage) + log10(ExpenditureYear0),
##     data = df0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.539 -12.120   3.539  11.659  28.879
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -1032.55     202.39  -5.102 7.25e-06 ***
## log10(Youth)              195.90      89.76   2.182  0.03458 *
## log10(BelowWage)          134.11      44.18   3.035  0.00407 **
## log10(ExpenditureYear0)   215.46      24.88   8.659 5.64e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.83 on 43 degrees of freedom
## Multiple R-squared:  0.6441, Adjusted R-squared:  0.6193
## F-statistic: 25.94 on 3 and 43 DF,  p-value: 9.768e-10
```

```
anova(lm.fit3, lm.fit4)
```

```
## Analysis of Variance Table
##
## Model 1: CrimeRate ~ +log10(Youth) + log10(Wage) + log10(BelowWage) +
##     log10(ExpenditureYear0)
## Model 2: CrimeRate ~ +log10(Youth) + log10(BelowWage) + log10(ExpenditureYear0)
##   Res.Df   RSS Df Sum of Sq      F Pr(>F)
## 1     42 12231
## 2     43 13668 -1   -1436.5 4.9328 0.0318 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

References:

1. US Census