Lab 4

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TODO: As this is a policy exercise, you should do your best to address the campaign's questions from a causal perspective. At the same time, you should clearly explain the limitations of your analysis, and provide discussion around whether your estimates suffer from endogeneity bias.

Introduction

TODO: A brief introduction

Exploratory Data Analysis

TODO: An initial exploratory analysis. Detect any anomalies, including missing values, top-coded or bottom-coded variables, etc.

```
library(car) # lm
library(ggplot2) # ggplot
library(lmtest) # bptest
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
library(plm) # vcovHC
```

```
## Loading required package: Formula
```

```
library(sandwich)
library(stargazer) # stargazer
```

```
##
## Please cite as:
```

```
##  Hlavac, Marek (2015). stargazer: Well-Formatted Regression and Summary Statistics Tables.
```

```
##  R package version 5.2. http://CRAN.R-project.org/package=stargazer
```

```
library(tidyr) # gather
```

```
data <- read.csv("crime.csv")
str(data)
```

```
## 'data.frame':    90 obs. of  26 variables:
##  $ X       : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ county  : int  1 3 5 7 9 11 13 15 17 19 ...
##  $ year    : int  87 87 87 87 87 87 87 87 87 87 ...
```

```
##  $ crmrte  : num  0.0356 0.0153 0.013 0.0268 0.0106 ...
##  $ prbarr  : num  0.298 0.132 0.444 0.365 0.518 ...
##  $ prbconv : num  0.528 1.481 0.268 0.525 0.477 ...
##  $ prbpris : num  0.436 0.45 0.6 0.435 0.443 ...
##  $ avgsen  : num  6.71 6.35 6.76 7.14 8.22 ...
##  $ polpc   : num  0.001828 0.000746 0.001234 0.00153 0.00086 ...
##  $ density : num  2.423 1.046 0.413 0.492 0.547 ...
##  $ taxpc   : num  31 26.9 34.8 42.9 28.1 ...
##  $ west    : int  0 0 1 0 1 1 0 0 0 0 ...
##  $ central : int  1 1 0 1 0 0 0 0 0 0 ...
##  $ urban   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ pctmin80: num  20.22 7.92 3.16 47.92 1.8 ...
##  $ wcon    : num  281 255 227 375 292 ...
##  $ wtuc    : num  409 376 372 398 377 ...
##  $ wtrd    : num  221 196 229 191 207 ...
##  $ wfir    : num  453 259 306 281 289 ...
##  $ wser    : num  274 192 210 257 215 ...
##  $ wmfg    : num  335 300 238 282 291 ...
##  $ wfed    : num  478 410 359 412 377 ...
##  $ wsta    : num  292 363 332 328 367 ...
##  $ wloc    : num  312 301 281 299 343 ...
##  $ mix     : num  0.0802 0.0302 0.4651 0.2736 0.0601 ...
##  $ pctymle : num  0.0779 0.0826 0.0721 0.0735 0.0707 ...
```

```
summary(data)
```

```
##        X             county           year        crmrte
##  Min.   : 1.00   Min.   :  1.0   Min.   :87   Min.   :0.005533
##  1st Qu.:23.25   1st Qu.: 51.5   1st Qu.:87   1st Qu.:0.020604
##  Median :45.50   Median :103.0   Median :87   Median :0.030002
##  Mean   :45.50   Mean   :100.6   Mean   :87   Mean   :0.033510
##  3rd Qu.:67.75   3rd Qu.:150.5   3rd Qu.:87   3rd Qu.:0.040249
##  Max.   :90.00   Max.   :197.0   Max.   :87   Max.   :0.098966
##      prbarr           prbconv           prbpris           avgsen
##  Min.   :0.09277   Min.   :0.06838   Min.   :0.1500   Min.   : 5.380
##  1st Qu.:0.20495   1st Qu.:0.34422   1st Qu.:0.3642   1st Qu.: 7.375
##  Median :0.27146   Median :0.45170   Median :0.4222   Median : 9.110
##  Mean   :0.29524   Mean   :0.55086   Mean   :0.4106   Mean   : 9.689
##  3rd Qu.:0.34487   3rd Qu.:0.58513   3rd Qu.:0.4576   3rd Qu.:11.465
##  Max.   :1.09091   Max.   :2.12121   Max.   :0.6000   Max.   :20.700
##      polpc              density           taxpc             west
##  Min.   :0.0007459   Min.   :0.2034   Min.   : 25.69   Min.   :0.0000
##  1st Qu.:0.0012378   1st Qu.:0.5472   1st Qu.: 30.73   1st Qu.:0.0000
##  Median :0.0014897   Median :0.9792   Median : 34.92   Median :0.0000
##  Mean   :0.0017080   Mean   :1.4379   Mean   : 38.16   Mean   :0.2333
##  3rd Qu.:0.0018856   3rd Qu.:1.5693   3rd Qu.: 41.01   3rd Qu.:0.0000
##  Max.   :0.0090543   Max.   :8.8277   Max.   :119.76   Max.   :1.0000
##     central           urban            pctmin80          wcon
##  Min.   :0.0000   Min.   :0.00000   Min.   : 1.284   Min.   :193.6
##  1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:10.024   1st Qu.:250.8
##  Median :0.0000   Median :0.00000   Median :24.852   Median :281.2
##  Mean   :0.3778   Mean   :0.08889   Mean   :25.713   Mean   :285.4
##  3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:38.183   3rd Qu.:315.0
##  Max.   :1.0000   Max.   :1.00000   Max.   :64.348   Max.   :436.8
##       wtuc             wtrd             wfir             wser
```

```
##  Min.   :187.6   Min.   :154.2   Min.   :170.9   Min.   : 133.0
##  1st Qu.:374.3   1st Qu.:190.7   1st Qu.:285.6   1st Qu.: 229.3
##  Median :404.8   Median :203.0   Median :317.1   Median : 253.1
##  Mean   :410.9   Mean   :210.9   Mean   :321.6   Mean   : 275.3
##  3rd Qu.:440.7   3rd Qu.:224.3   3rd Qu.:342.6   3rd Qu.: 277.6
##  Max.   :613.2   Max.   :354.7   Max.   :509.5   Max.   :2177.1
##       wmfg            wfed            wsta            wloc
##  Min.   :157.4   Min.   :326.1   Min.   :258.3   Min.   :239.2
##  1st Qu.:288.6   1st Qu.:398.8   1st Qu.:329.3   1st Qu.:297.2
##  Median :321.1   Median :448.9   Median :358.4   Median :307.6
##  Mean   :336.0   Mean   :442.6   Mean   :357.7   Mean   :312.3
##  3rd Qu.:359.9   3rd Qu.:478.3   3rd Qu.:383.2   3rd Qu.:328.8
##  Max.   :646.9   Max.   :598.0   Max.   :499.6   Max.   :388.1
##       mix             pctymle
##  Min.   :0.01961   Min.   :0.06216
##  1st Qu.:0.08060   1st Qu.:0.07437
##  Median :0.10095   Median :0.07770
##  Mean   :0.12905   Mean   :0.08403
##  3rd Qu.:0.15206   3rd Qu.:0.08352
##  Max.   :0.46512   Max.   :0.24871
```

```
# sample size n = 90
nrow(data)
```

```
## [1] 90
```

```
# number of variables = 26
ncol(data)
```

```
## [1] 26
```

```
# number of prbarr where probability is greater than 1
sum(data$prbarr > 1)
```

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

```
# number of prbconv where probability is greater than 1
sum(data$prbconv > 1)
```

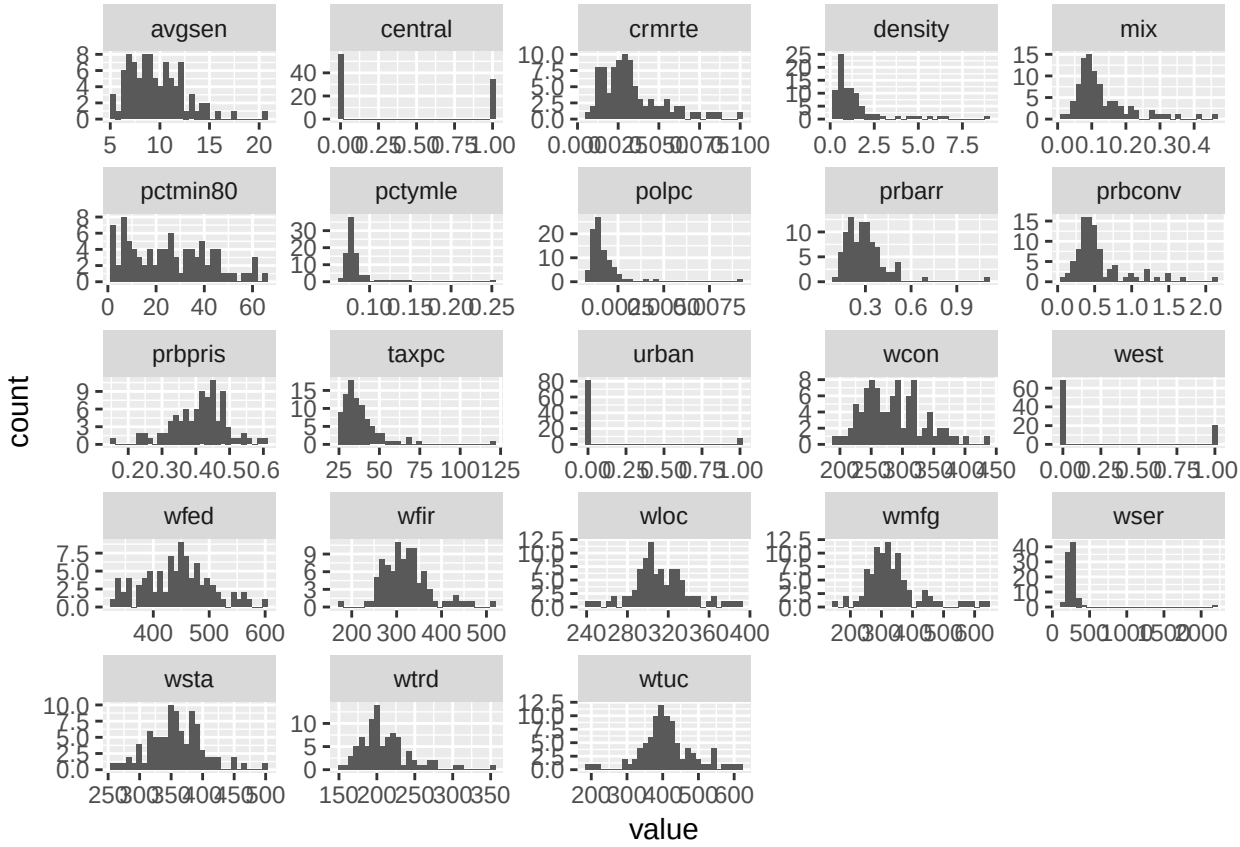
```
## [1] 10
```

```
# verify number of missing values = 0
colSums(sapply(data, is.na))
```

```
##        X   county     year   crmrte   prbarr  prbconv  prbpris   avgsen
##        0        0        0        0        0        0        0        0
##    polpc  density    taxpc     west  central    urban pctmin80     wcon
##        0        0        0        0        0        0        0        0
##     wtuc     wtrd     wfir     wser     wmfg     wfed     wsta     wloc
##        0        0        0        0        0        0        0        0
##      mix  pctymle
##        0        0
```

```
# plot every variable except x, county, year
plot.data <- data[!(names(data) %in% c("X", "county", "year"))]
ggplot(gather(plot.data), aes(value)) +
       facet_wrap(~key, scales="free") +
       geom_histogram()
```

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




```
# just list outliers for variables that are non-categorical
subset.data <- data[!(names(data) %in% c("X", "county", "year", "central", "urban", "west"))]

# list all outliers
list_all_outliers <- function (var) {
  outliers <- sort(boxplot.stats(var)$out)
  return(paste(length(outliers), ": ", paste(outliers, collapse=", ")))
}
lapply(subset.data, list_all_outliers)
```

```
## $crmrte
## [1] "5 :  0.0729478970170021, 0.0790162980556488, 0.0834982022643089, 0.0883848965167999, 0.09896589
##
## $prbarr
## [1] "2 :  0.689023971557617, 1.09090995788574"
##
## $prbconv
## [1] "11 :  0.972972989082336, 1.01538002490997, 1.06896996498108, 1.18292999267578, 1.22561001777649
##
## $prbpris
## [1] "1 :  0.150000005960464"
##
## $avgsen
## [1] "1 :  20.7000007629395"
##
```

```
## $polpc
## [1] "4 :  0.00316379009746015, 0.00400961982086301, 0.00445923022925854, 0.00905433017760515"
##
## $density
## [1] "8 :  3.93455100059509, 4.38875865936279, 4.8347339630127, 5.12442398071289, 5.6744966506958, 6.1
##
## $taxpc
## [1] "6 :  56.8621063232422, 61.1525115966797, 67.6796340942383, 67.8479766845703, 75.6724319458008,
##
## $pctmin80
## [1] "0 :  "
##
## $wcon
## [1] "1 :  436.766632080078"
##
## $wtuc
## [1] "9 :  187.617263793945, 202.429153442383, 213.675216674805, 548.323852539062, 548.986511230469, 5
##
## $wtrd
## [1] "5 :  277.292510986328, 279.227264404297, 306.083526611328, 308.576232910156, 354.676116943359"
##
## $wfir
## [1] "7 :  170.940170288086, 430.069702148438, 435.110717773438, 441.141296386719, 453.172210693359, 4
##
## $wser
## [1] "4 :  133.043060302734, 354.300720214844, 391.308074951172, 2177.06811523438"
##
## $wmfg
## [1] "7 :  157.410003662109, 494.299987792969, 560.780029296875, 567.059997558594, 588.989990234375, 6
##
## $wfed
## [1] "0 :  "
##
## $wsta
## [1] "1 :  499.589996337891"
##
## $wloc
## [1] "5 :  239.169998168945, 246.649993896484, 379.769989013672, 386.119995117188, 388.089996337891"
##
## $mix
## [1] "8 :  0.273622035980225, 0.28078818321228, 0.290488421916962, 0.311355322599411, 0.319526642560
##
## $pctymle
## [1] "10 :  0.0989191979169846, 0.0993558466434479, 0.106941692531109, 0.114216551184654, 0.122244790
```

Glaring outliers: 1. Probability > 1 for prbarr and prbconv 2. Outlier 2177 in wser which happens to be in central instead of urban (weird)

```
# number of urban
sum(data$urban == 1)
```

```
## [1] 8
```

```
# number of central
sum(data$central == 1)
```

```
## [1] 34
```

```
# number of west
sum(data$west == 1)
```

```
## [1] 21
```

```
# determine if a county can have multiple categorical label: urban, central, west
urban.county <- data[data$urban == 1, ]$county
central.county <- data[data$central == 1, ]$county
west.county <- data[data$west == 1, ]$county
# can a county be labeled as both urban and central?
uc.county <- c(urban.county, central.county)
uc.county[duplicated(uc.county)]
```

```
## [1]  63  67  81 119 183
```

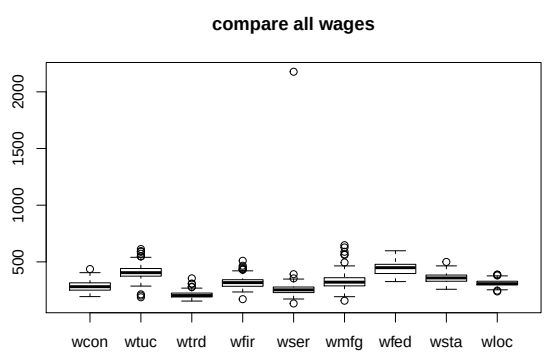
```
# can a county be labeled as both urban and west?
uw.county <- c(urban.county, west.county)
uw.county[duplicated(uw.county)]
```

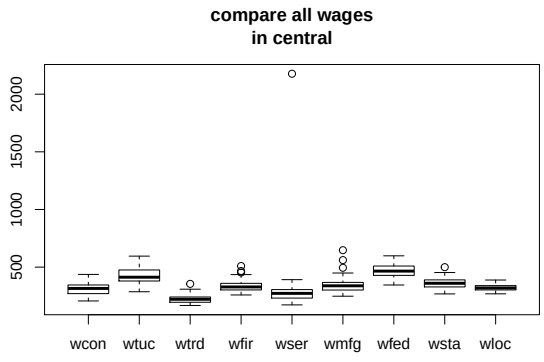
```
## [1] 21
```

```
# I have verified that there is no county labeled as both central and west
# counties that have more than one categorical label
all.county <- c(urban.county, central.county, west.county)
all.county[duplicated(all.county)]
```

```
## [1]  63  67  81 119 183  21
```

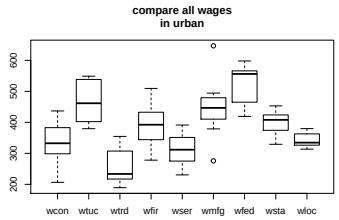
```
# compare all the wages
boxplot(as.vector(data[c(16:24)]), main="compare all wages")
# compare all wages in central
central.data <- data[data$central == 1, ]
boxplot(as.vector(central.data[c(16:24)]), main="compare all wages\nin central")
```

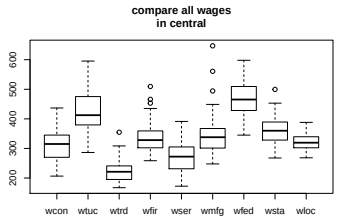


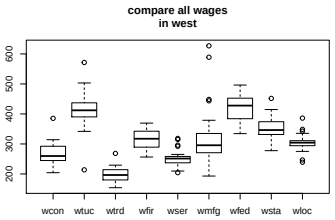


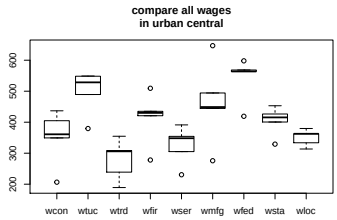

```
# compare all wages in urban
urban.data <- data[data$urban == 1, ]
boxplot(as.vector(urban.data[c(16:24)]), main="compare all wages\nin urban")
# compare all wages in central with outlier removed
central.data[central.data$wser == 2177.06811523438, ]$wser <- mean(central.data$wser)
boxplot(as.vector(central.data[c(16:24)]), main="compare all wages\nin central")
# compare all wages in west
west.data <- data[data$west == 1, ]
```

```r
boxplot(as.vector(west.data[c(16:24)]), main="compare all wages\nin west")
# compare all wages in urban and central
urban.central.data <- data[data$urban == 1 & data$central == 1, ]
boxplot(as.vector(urban.central.data[c(16:24)]), main="compare all wages\nin urban central")
# compare all wages in urban and west
# not worth it because it's only one dataset
```



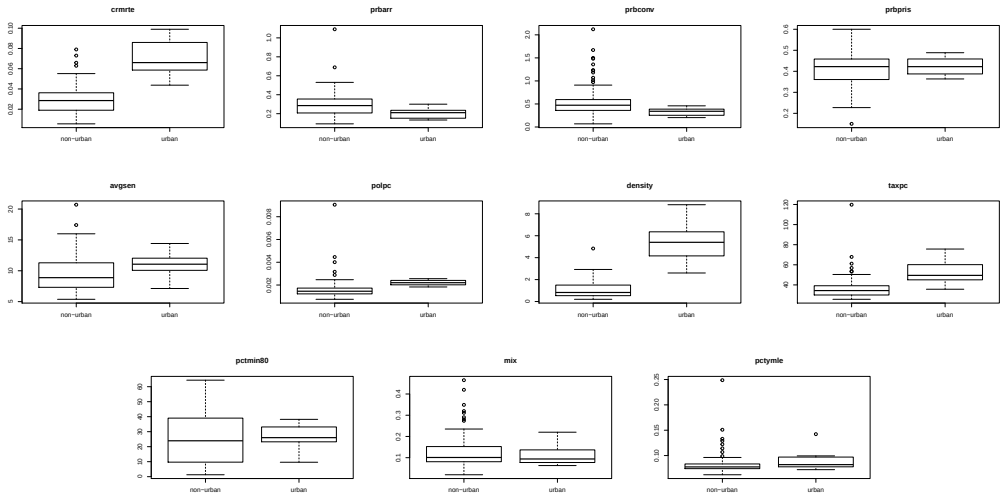




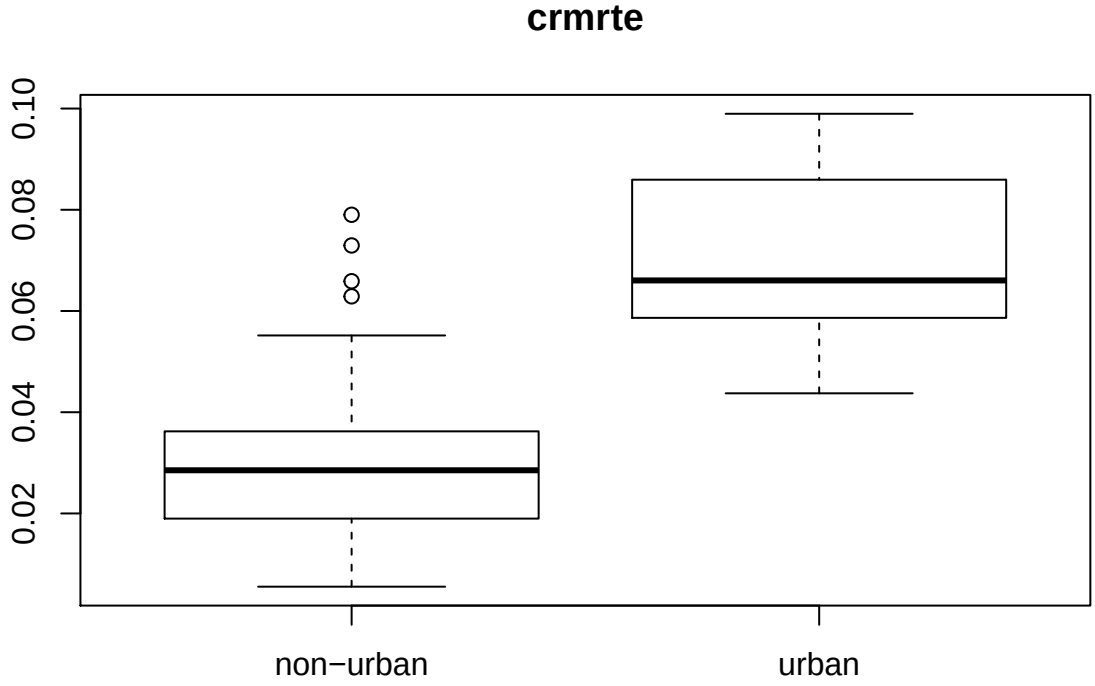


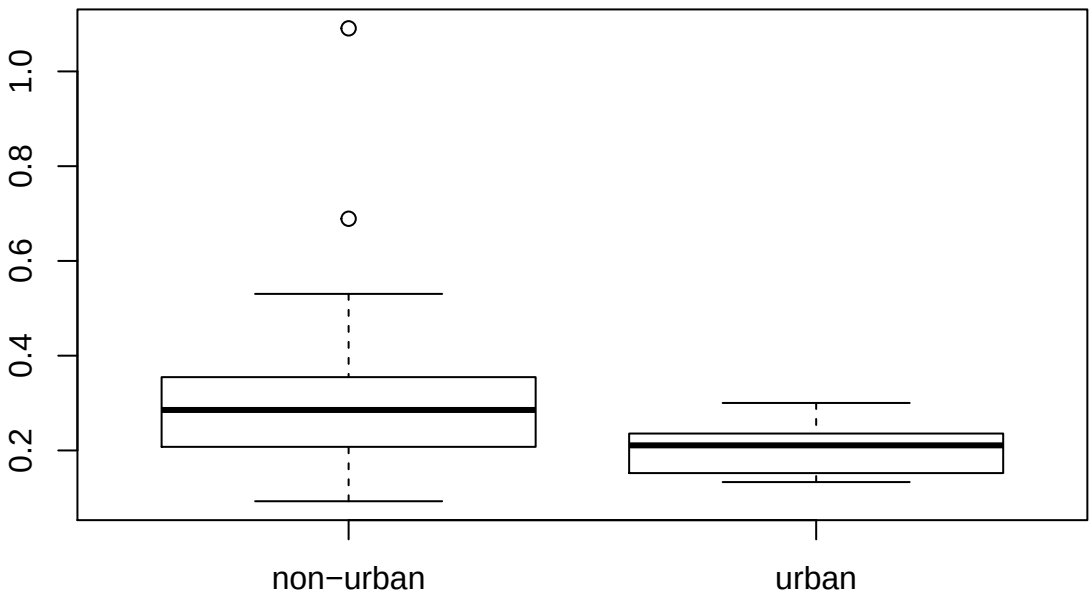

```r
# in urban area, is there higher ...?
independents <- c("crmrte", "prbarr", "prbconv", "prbpris", "avgsen", "polpc", "density", "taxpc", "pctm
mapply(function(var, var.name) {
  boxplot(var ~ urban, data=data, names=c("non-urban", "urban"), main=var.name)
}, subset(data, select=independents), independents)
```

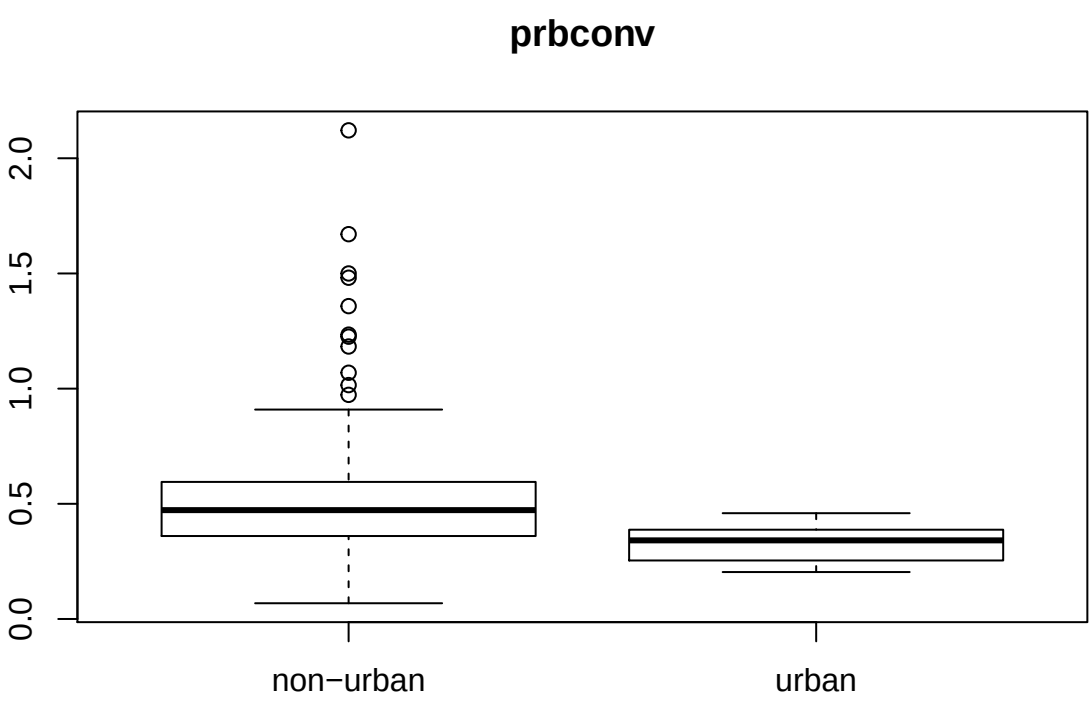
```
##       crmrte      prbarr      prbconv     prbpris     avgsen
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,4   Numeric,2   Numeric,11  0.15        Numeric,2
## group Numeric,4   Numeric,2   Numeric,11  1           Numeric,2
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       polpc       density     taxpc       pctmin80    mix
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,5   4.834734    Numeric,6   Numeric,0   Numeric,8
## group Numeric,5   1           Numeric,6   Numeric,0   Numeric,8
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       pctymle
## stats Numeric,10
## n     Numeric,2
## conf  Numeric,4
## out   Numeric,9
## group Numeric,9
## names Character,2
```

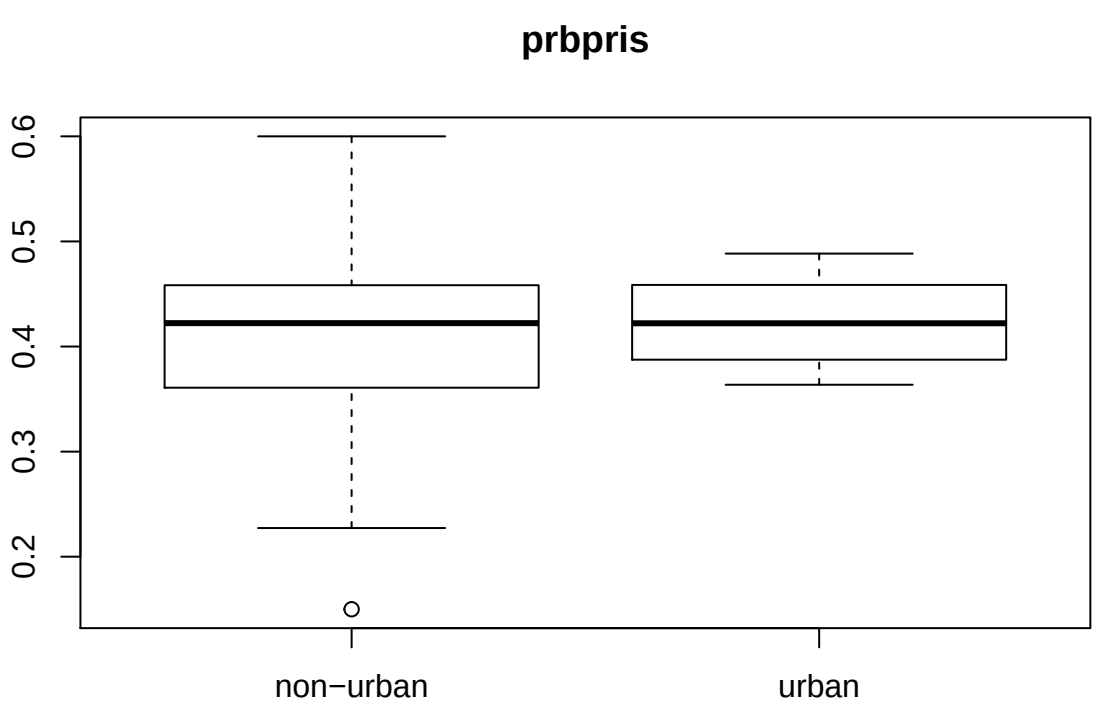


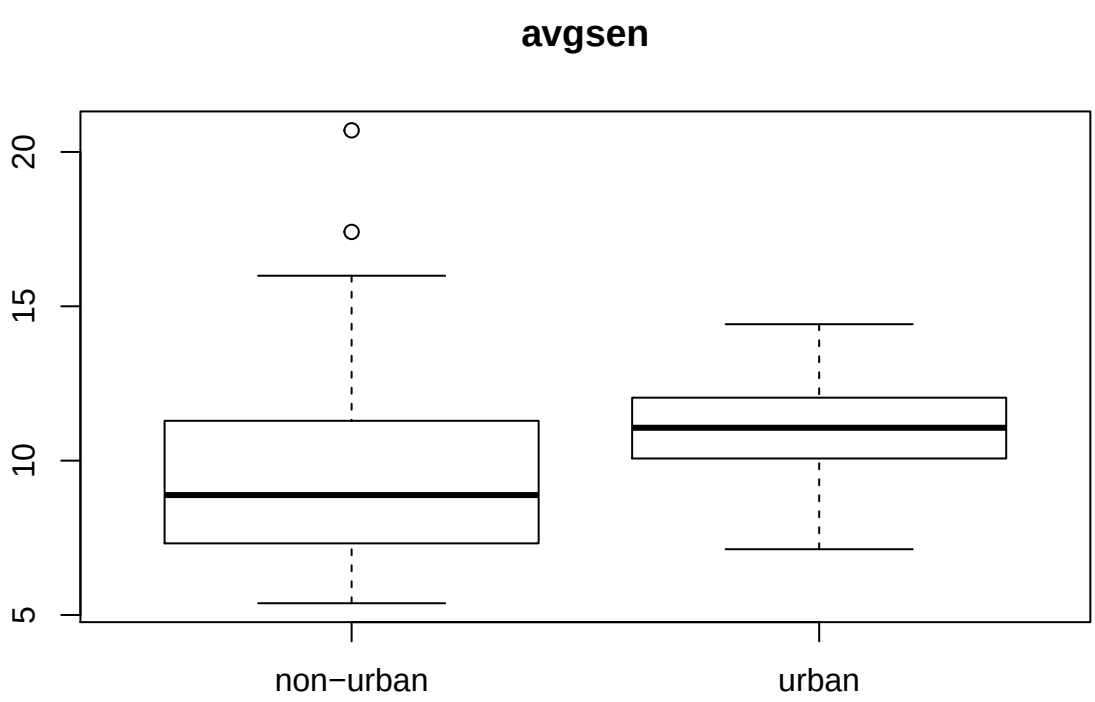

```
# repeat of above but checking out all the wages
mapply(function(var, var.name) {
  boxplot(var ~ urban, data=data, names=c("non-urban", "urban"), main=var.name)
}, subset.data, names(subset.data))
```

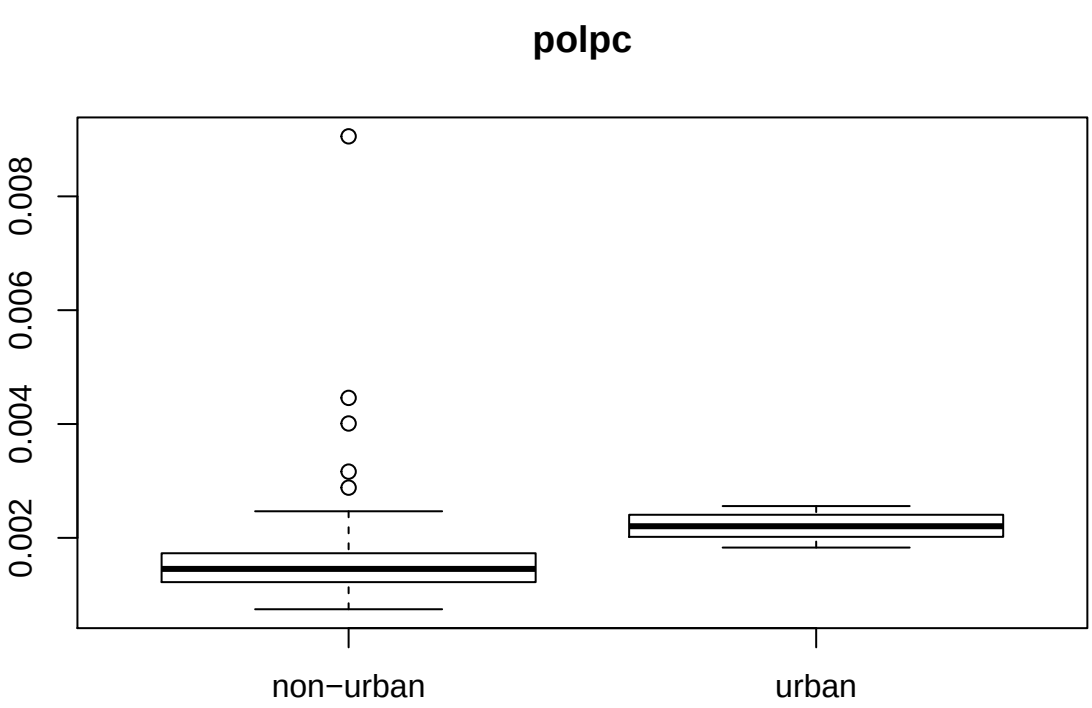


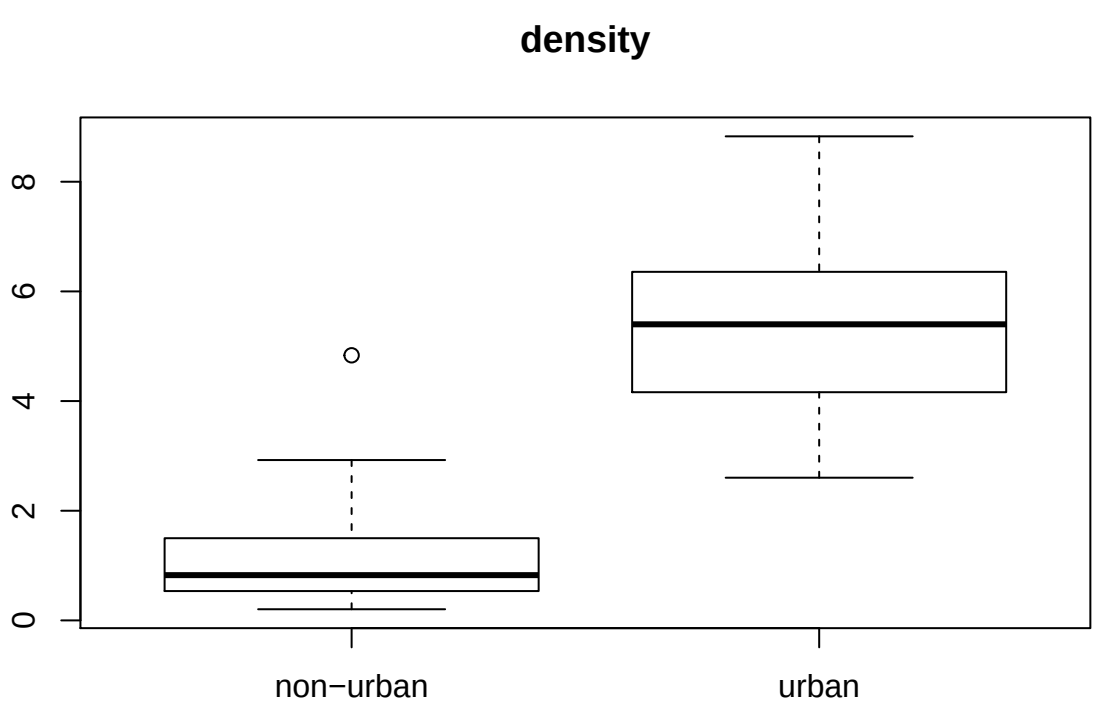

prbarr
0.2
0.4
0.6
0.8
1.0
non−urban
urban

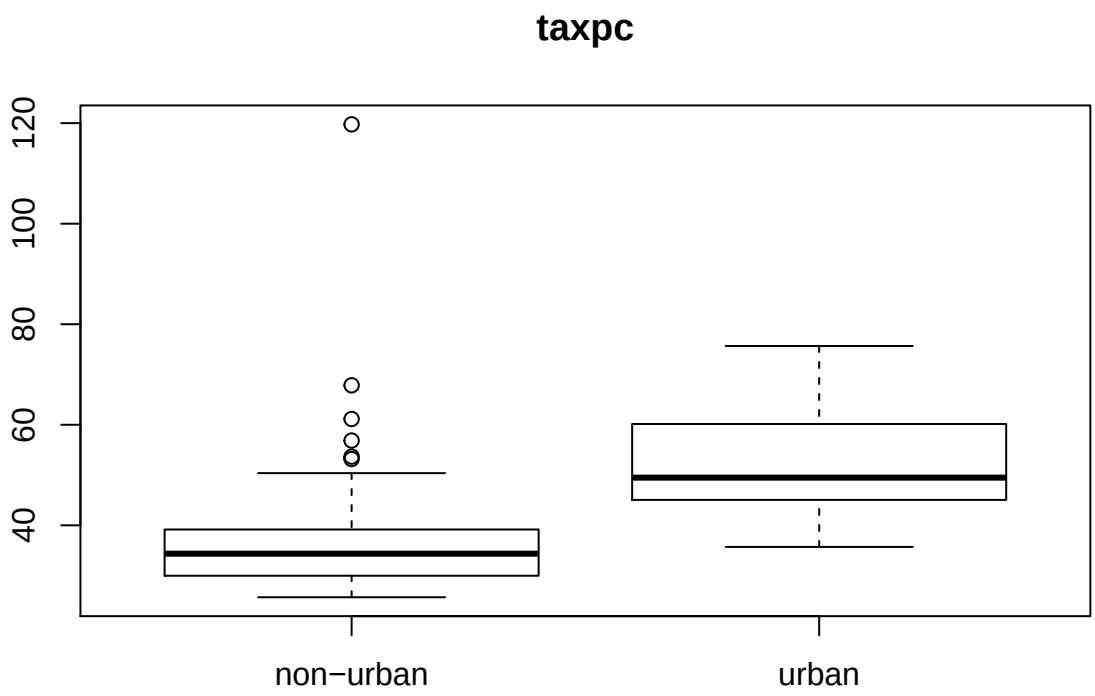

prbconv
0.0
0.5
1.0
1.5
2.0
non−urban
urban

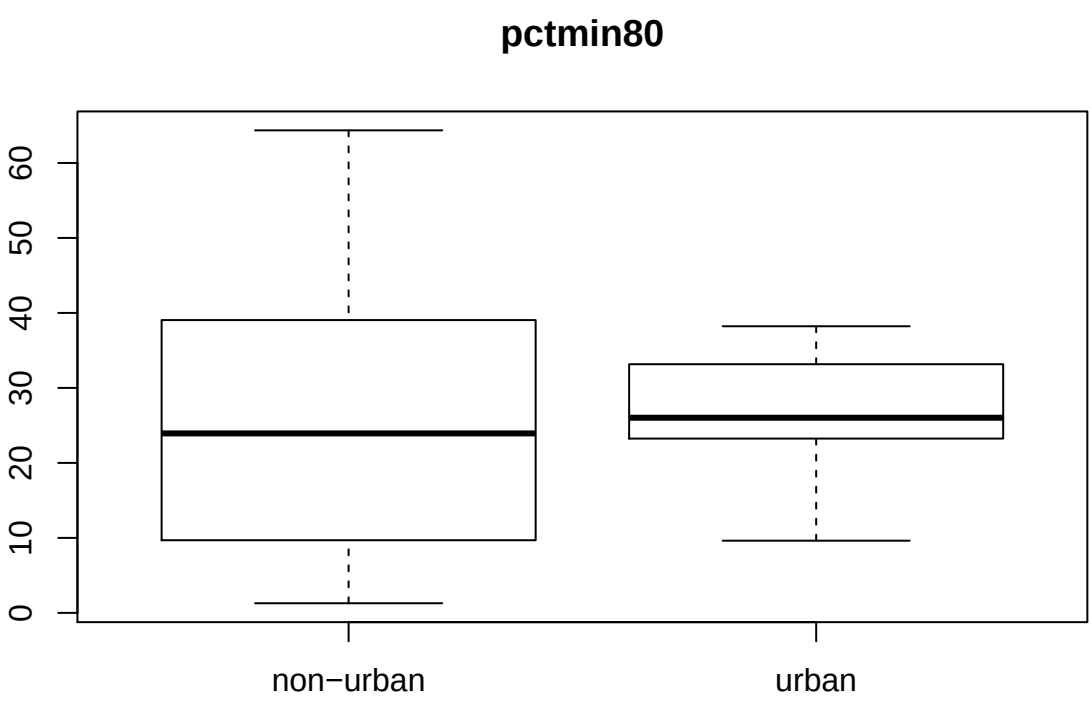

prbpris
0.2
0.3
0.4
0.5
0.6
non−urban
urban

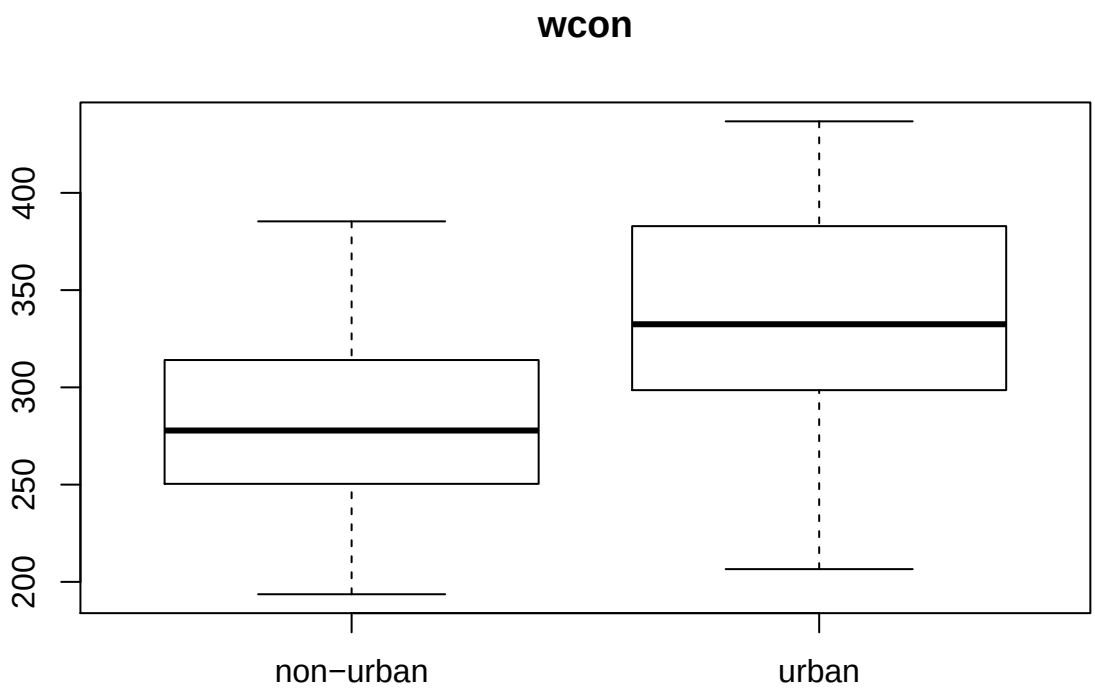

avgsen
20
15
10
5
non−urban
urban

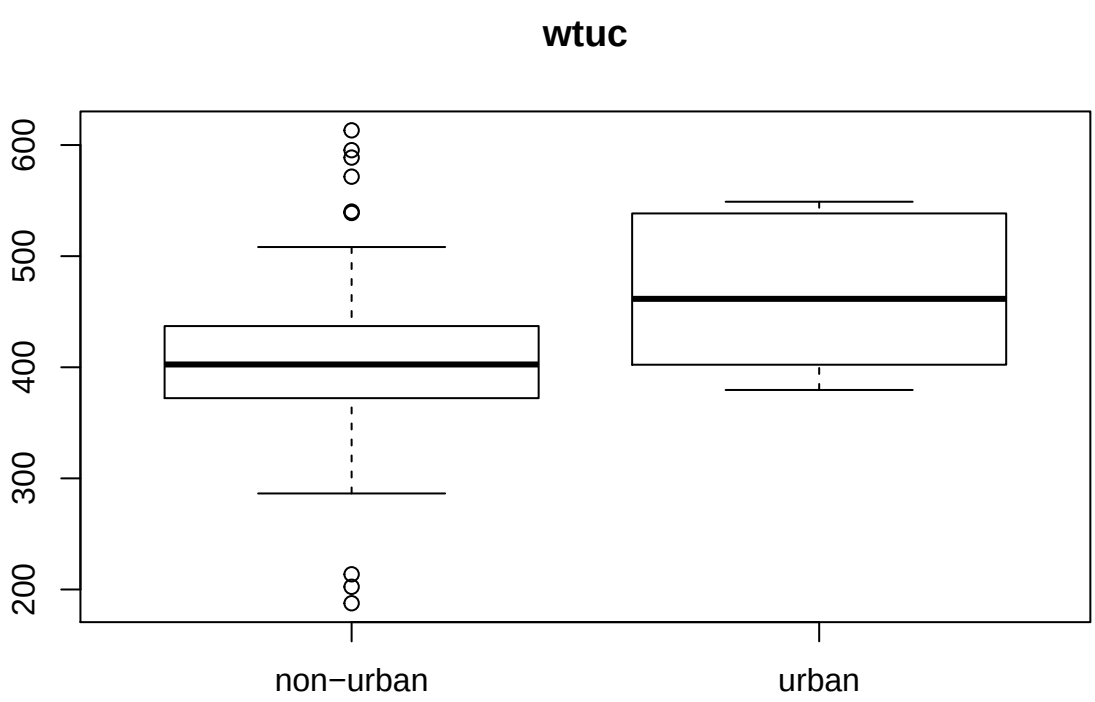

polpc
0.002
0.004
0.006
0.008
non−urban
urban

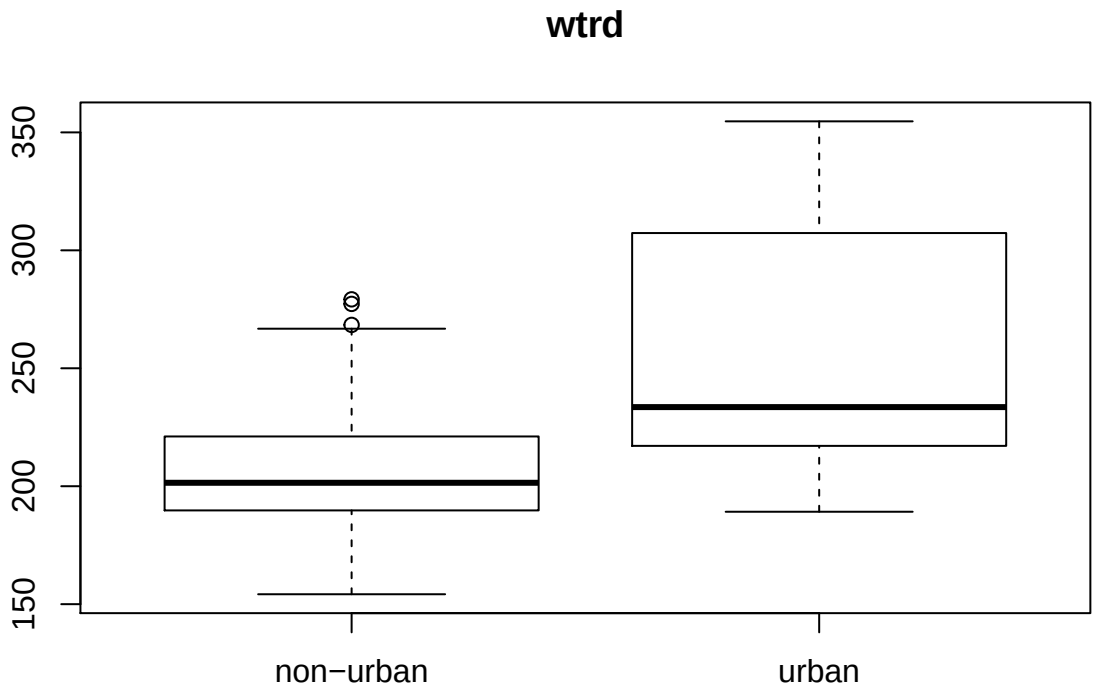

density
0
2
4
6
8
non−urban
urban

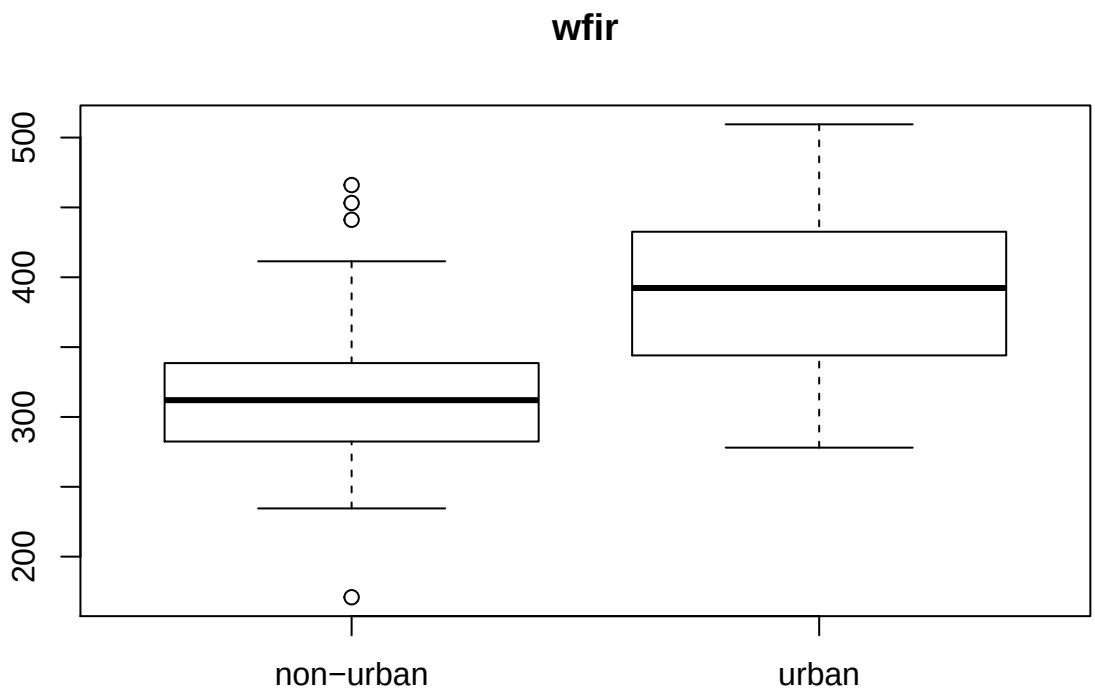

taxpc
120
100
80
60
40
non−urban
urban

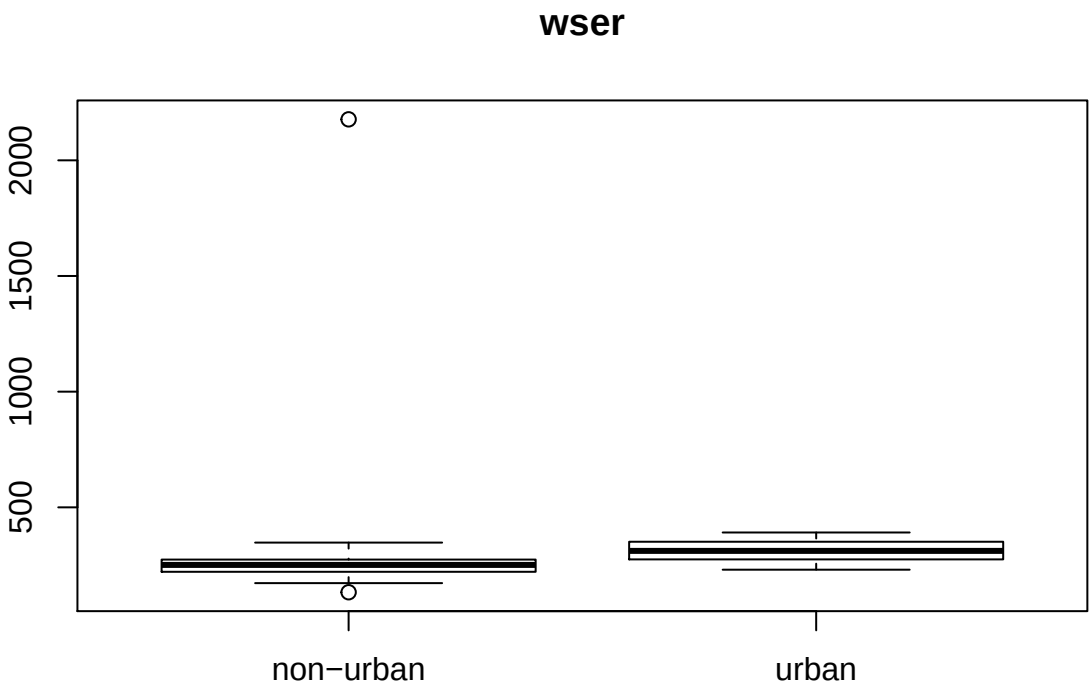

pctmin80
0
10
20
30
40
50
60
non−urban
urban

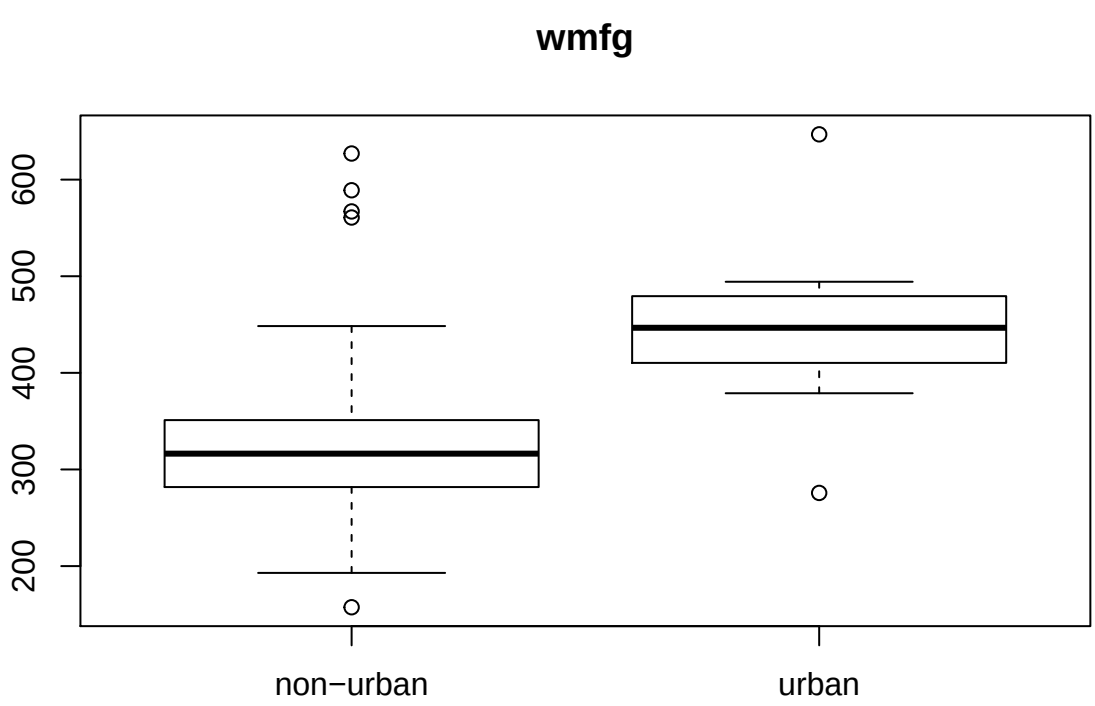

wcon
200
250
300
350
400
non−urban
urban

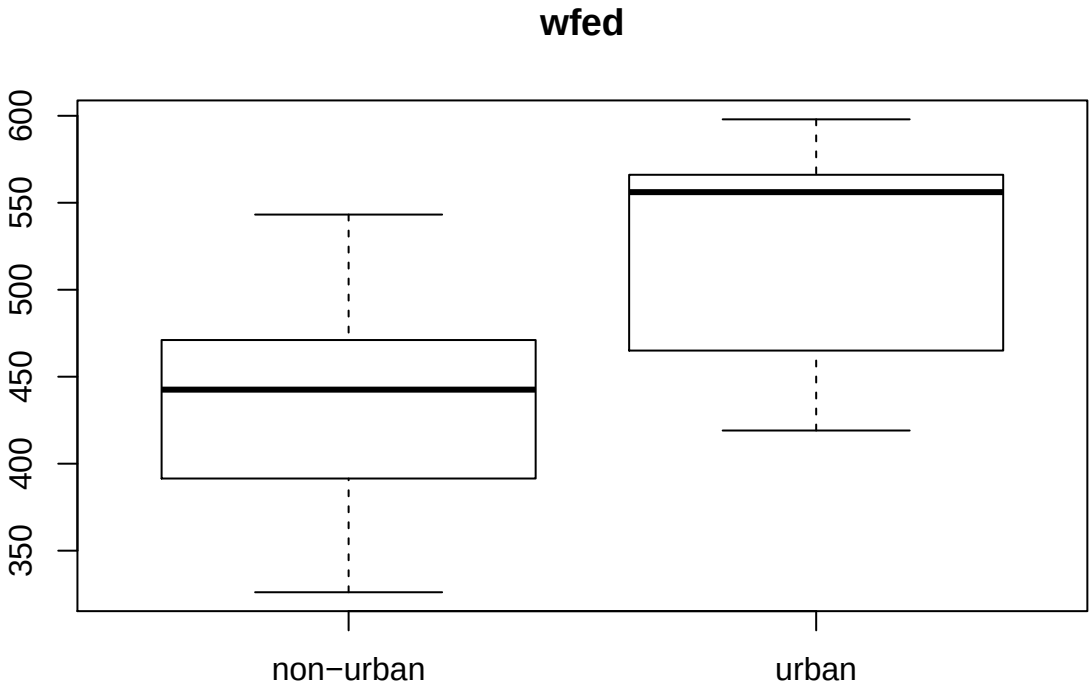

wtuc
600
500
400
300
200
non−urban
urban

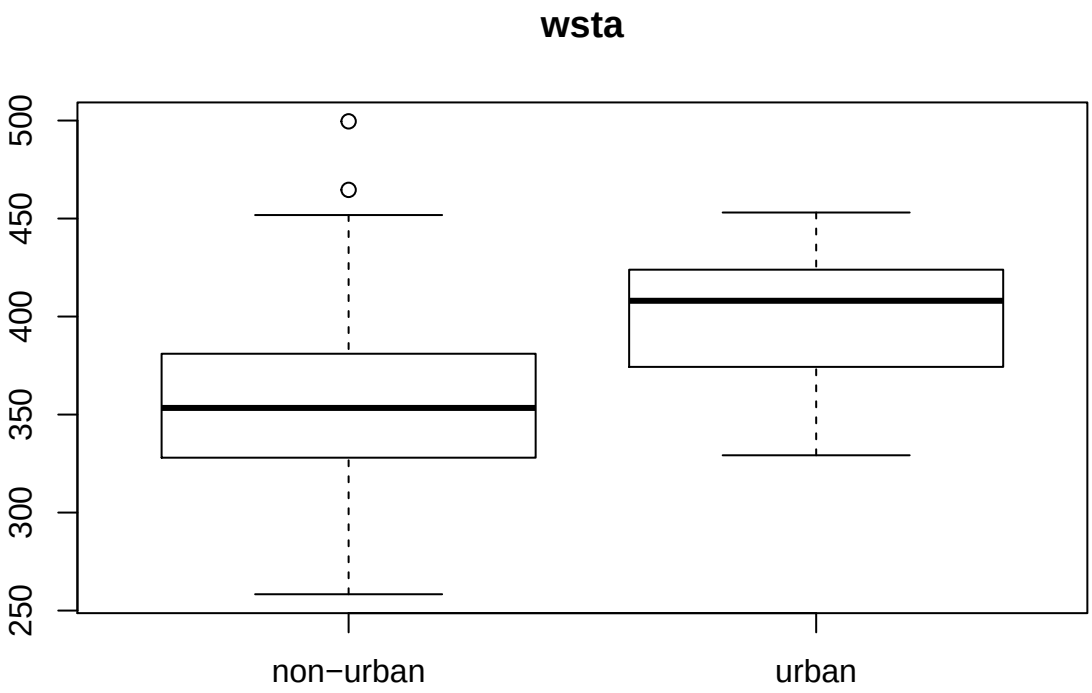

wtrd
350
300
250
200
150
non−urban
urban

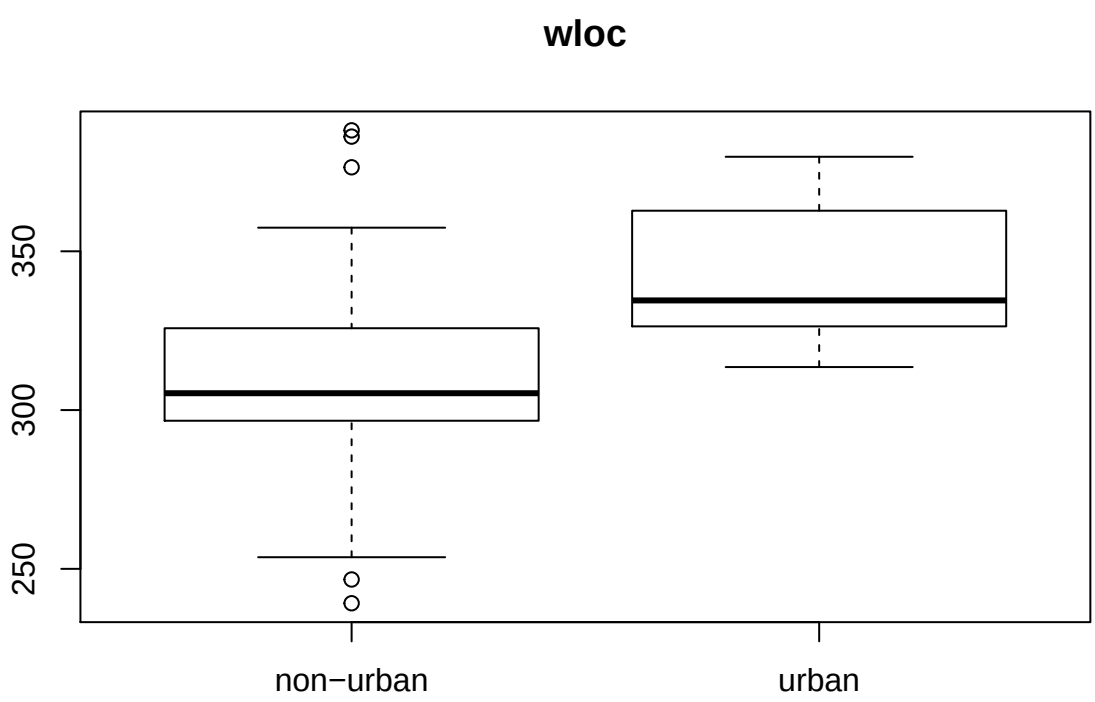

wfir
500
400
300
200
non−urban
urban

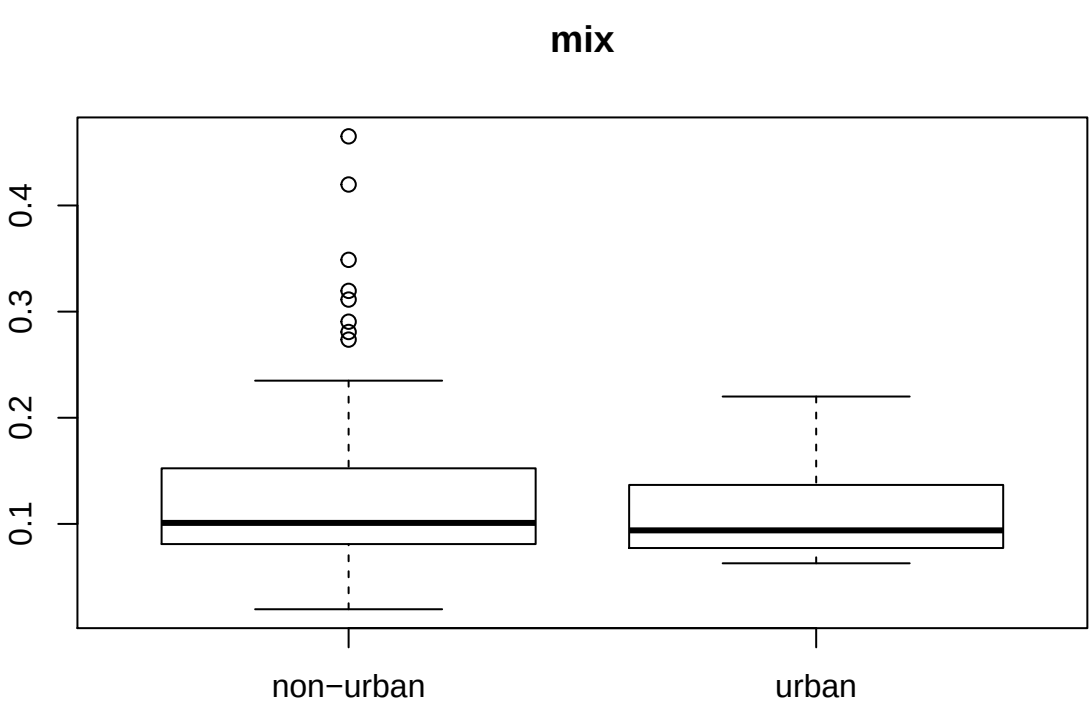

wser
500
1000
1500
2000
non−urban
urban

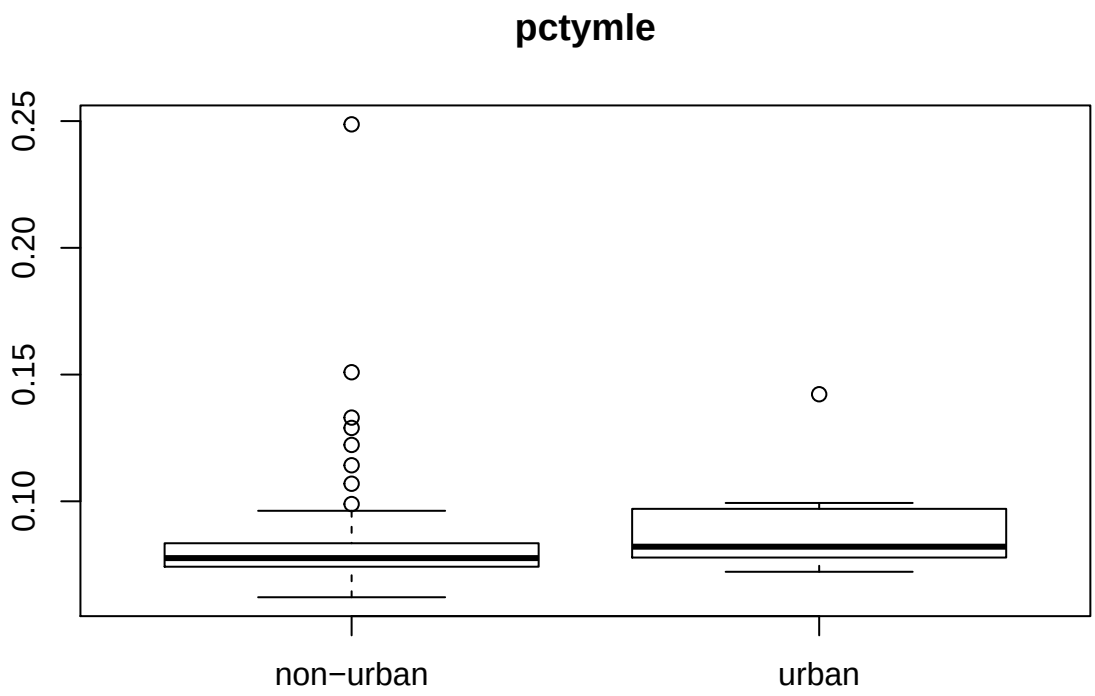

wmfg
200
300
400
500
600
non−urban
urban


wfed
600
550
500
450
400
350
non−urban
urban


wsta
500
450
400
350
300
250
non−urban
urban


wloc
350
300
250
non−urban
urban


mix
0.1
0.2
0.3
0.4
non−urban
urban




```
##       crmrte      prbarr      prbconv     prbpris     avgsen
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,4   Numeric,2   Numeric,11  0.15        Numeric,2
## group Numeric,4   Numeric,2   Numeric,11  1           Numeric,2
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       polpc       density     taxpc       pctmin80    wcon
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,5   4.834734    Numeric,6   Numeric,0   Numeric,0
## group Numeric,5   1           Numeric,6   Numeric,0   Numeric,0
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       wtuc        wtrd        wfir        wser        wmfg
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,9   Numeric,3   Numeric,4   Numeric,2   Numeric,7
## group Numeric,9   Numeric,3   Numeric,4   Numeric,2   Numeric,7
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       wfed        wsta        wloc        mix         pctymle
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,0   Numeric,2   Numeric,5   Numeric,8   Numeric,9
```

```
## group Numeric,0   Numeric,2   Numeric,5   Numeric,8   Numeric,9
## names Character,2 Character,2 Character,2 Character,2 Character,2
```

In urban areas, there is higher

- crime rates
- average sentence
- police per capita
- density
- tax revenue per capita
- percentage of minority (slightly higher but not much)
- percentage of young male (slightly higher but not much)
- wages tend to be higher overall

In urban areas, there is lower

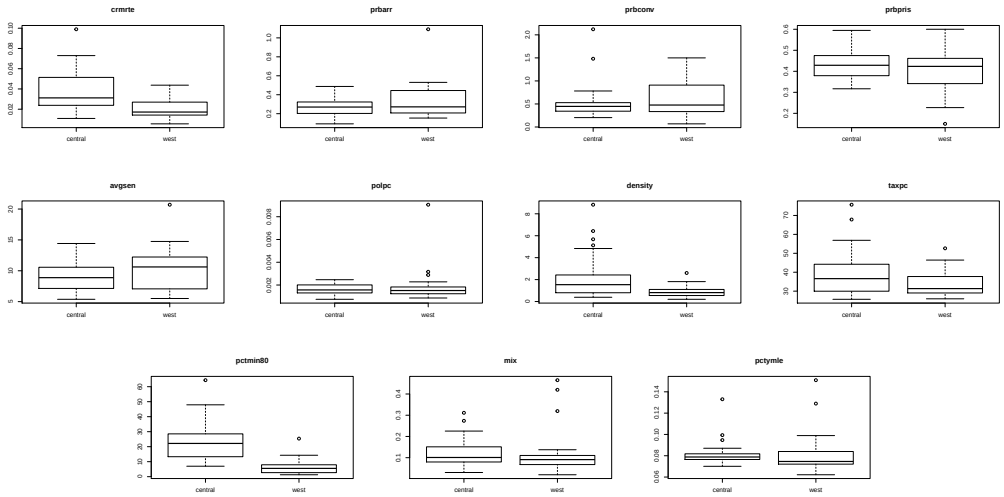
- probability of arrest
- probability of conviction
- face to face confrontation (slightly lower but not much)

In urban areas, there is about the same

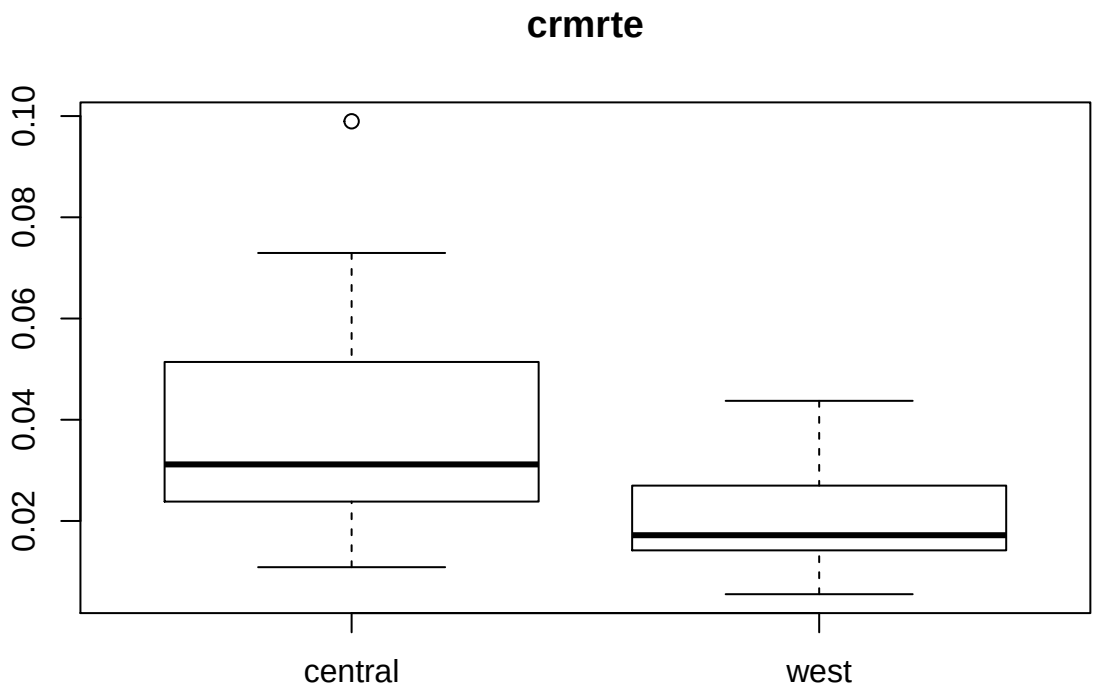
- probability of prison sentence

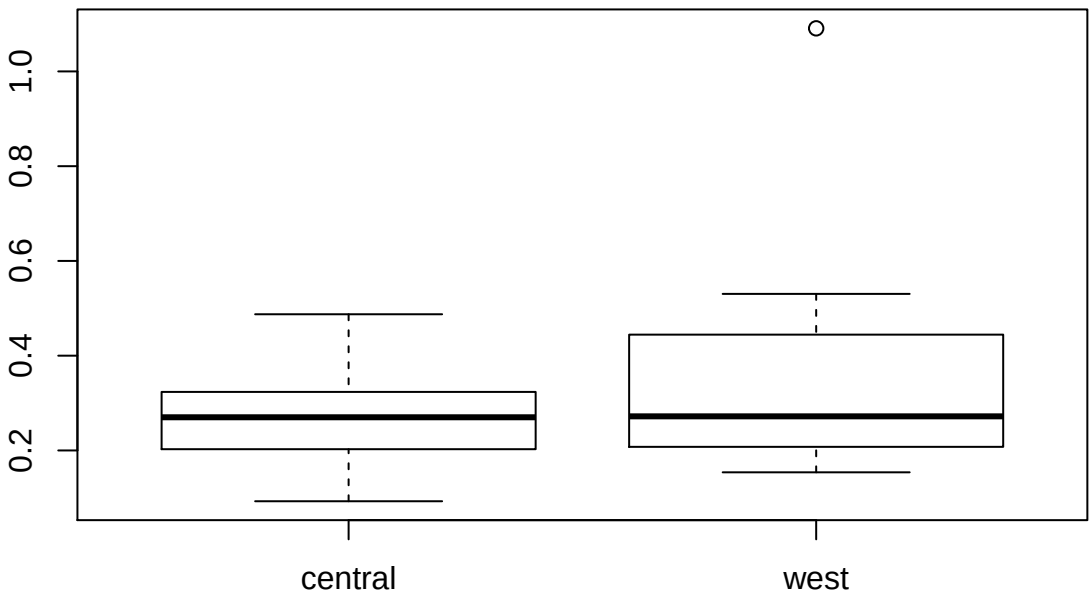
```
# comparing central and west, is there higher ...?
central.data <- data[data$central == 1, ]
subset.central.data <- subset(central.data, select=independents)
west.data <- data[data$west == 1, ]
subset.west.data <- subset(west.data, select=independents)
mapply(function(central.var, west.var, var.name) {
  boxplot(central.var, west.var, names=c("central", "west"), main=var.name)
}, subset.central.data, subset.west.data, independents)
```

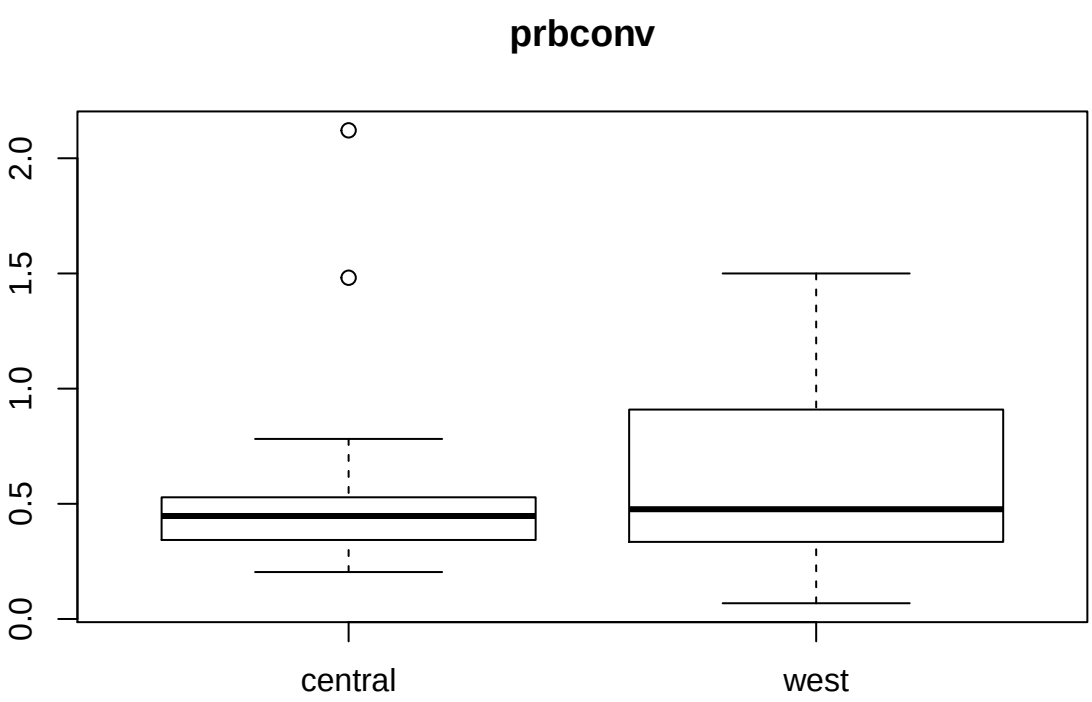
```
##       crmrte      prbarr      prbconv     prbpris     avgsen
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   0.0989659   1.09091     Numeric,2   0.15        20.7
## group 1           2           Numeric,2   2           2
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       polpc       density     taxpc       pctmin80    mix
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,3   Numeric,5   Numeric,3   Numeric,2   Numeric,5
## group Numeric,3   Numeric,5   Numeric,3   Numeric,2   Numeric,5
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       pctymle
## stats Numeric,10
## n     Numeric,2
## conf  Numeric,4
## out   Numeric,5
## group Numeric,5
## names Character,2
```

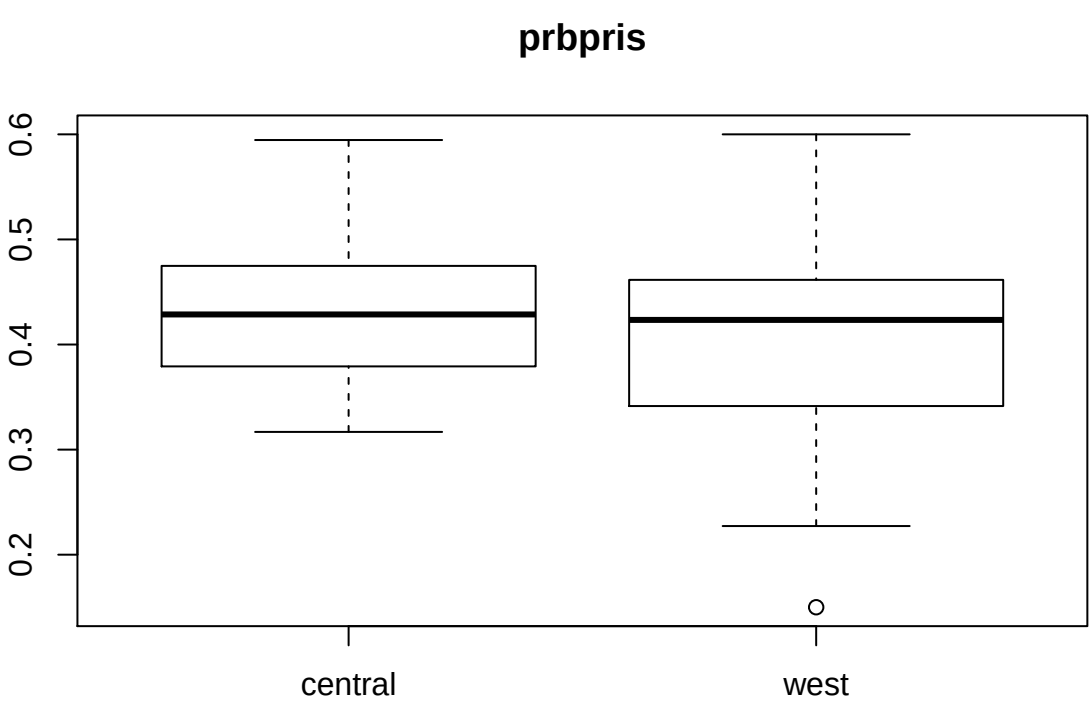


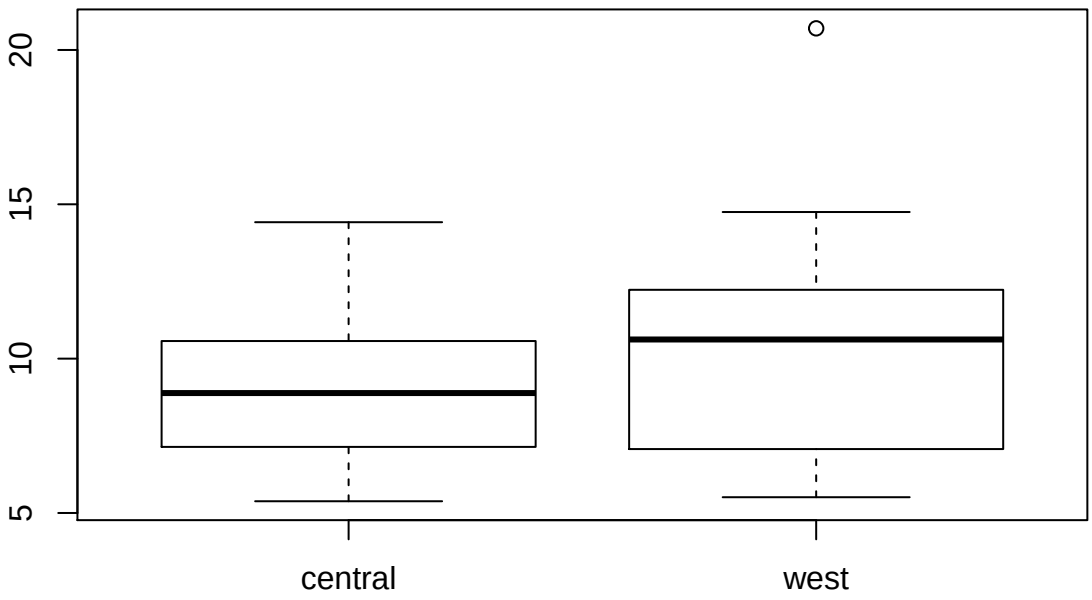

```
# repeat of above but checking out all the wages
central.data <- data[data$central == 1, ]
subset.central.data <- subset(central.data, select=names(subset.data))
west.data <- data[data$west == 1, ]
subset.west.data <- subset(west.data, select=names(subset.data))
mapply(function(central.var, west.var, var.name) {
  boxplot(central.var, west.var, names=c("central", "west"), main=var.name)
}, subset.central.data, subset.west.data, names(subset.data))
```

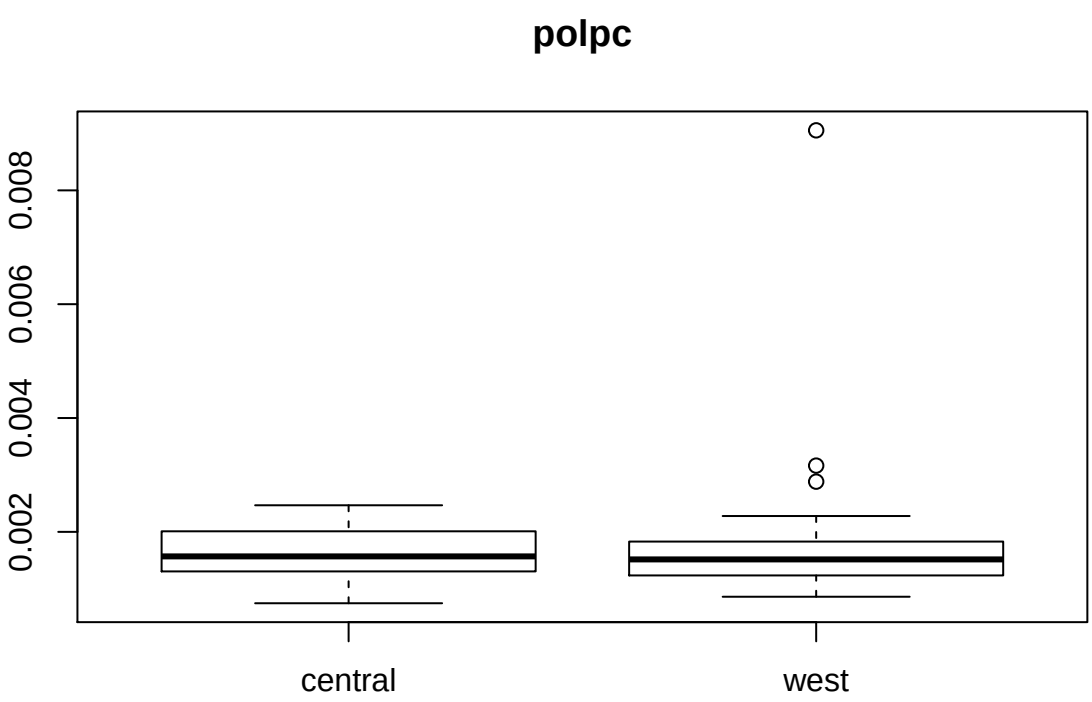


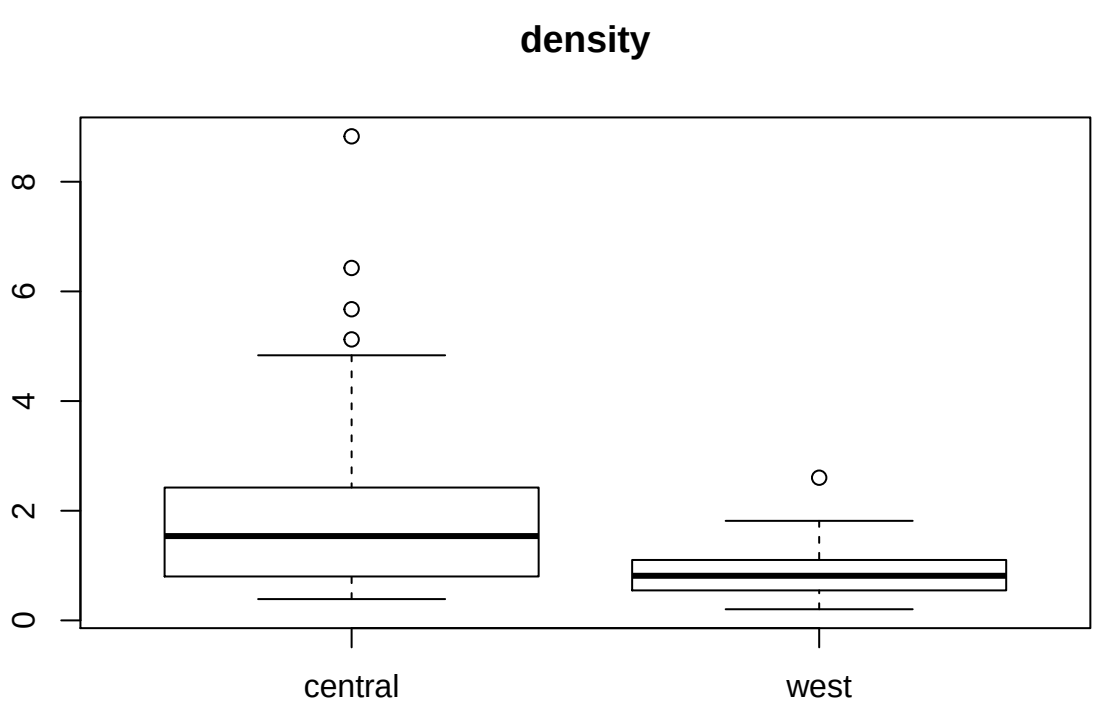

prbarr
0.2
0.4
0.6
0.8
1.0
central
west

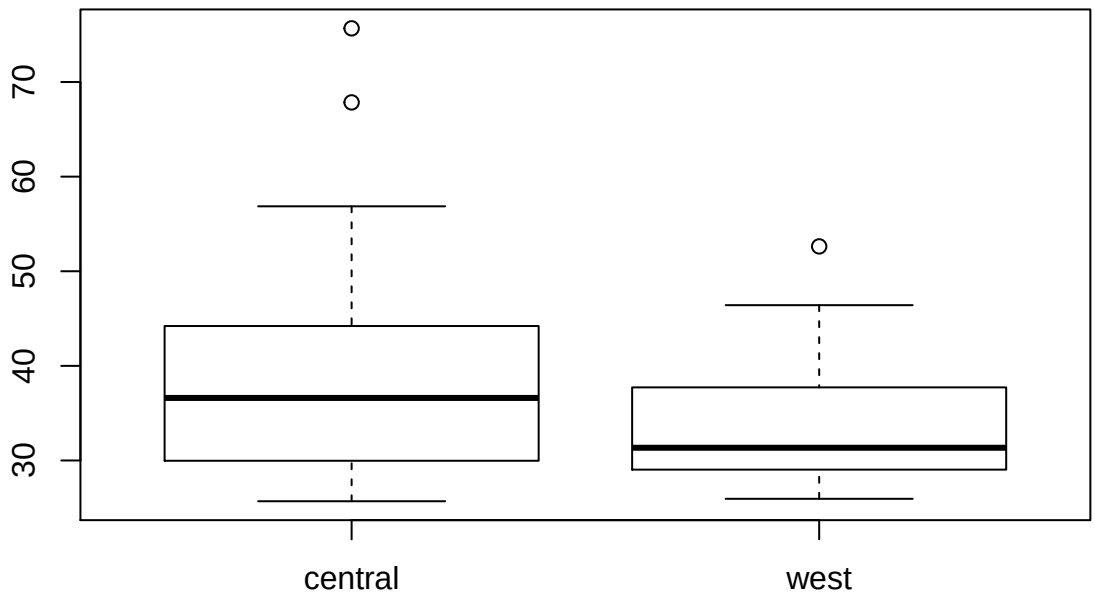

prbconv
0.0
0.5
1.0
1.5
2.0
central
west

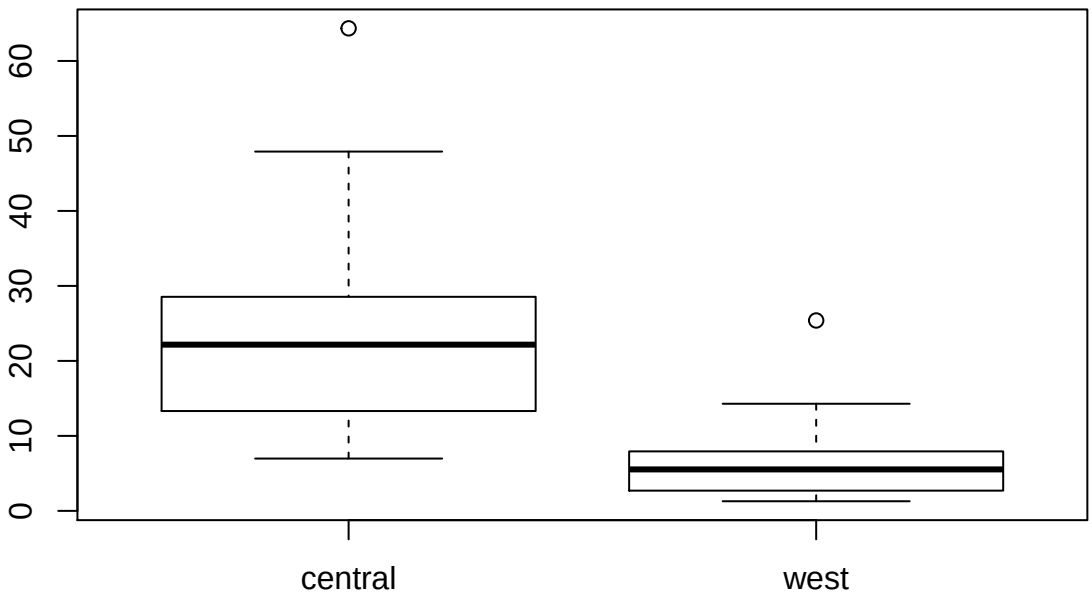

prbpris
0.2
0.3
0.4
0.5
0.6
central
west

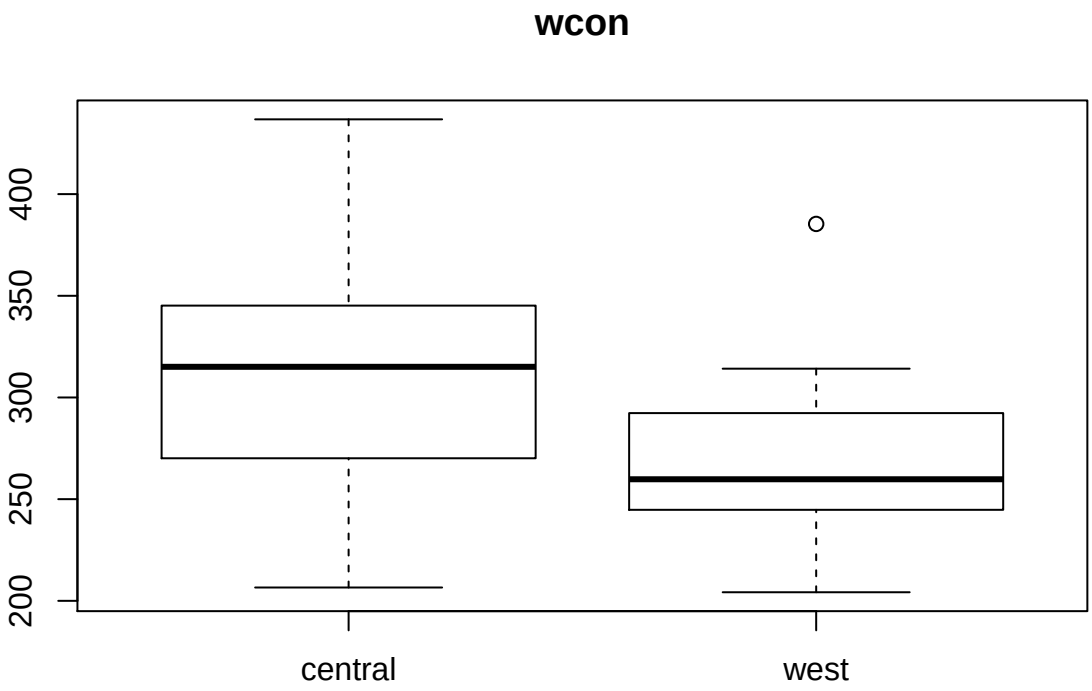

avgsen
20
15
10
5
central
west

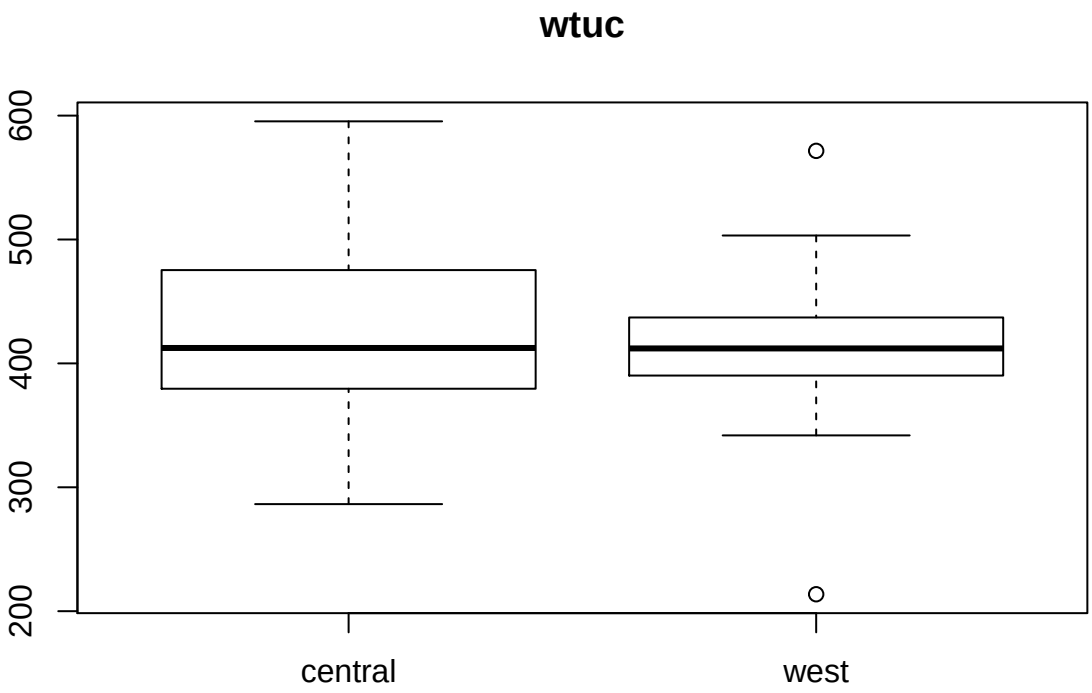

polpc
0.002
0.004
0.006
0.008
central
west

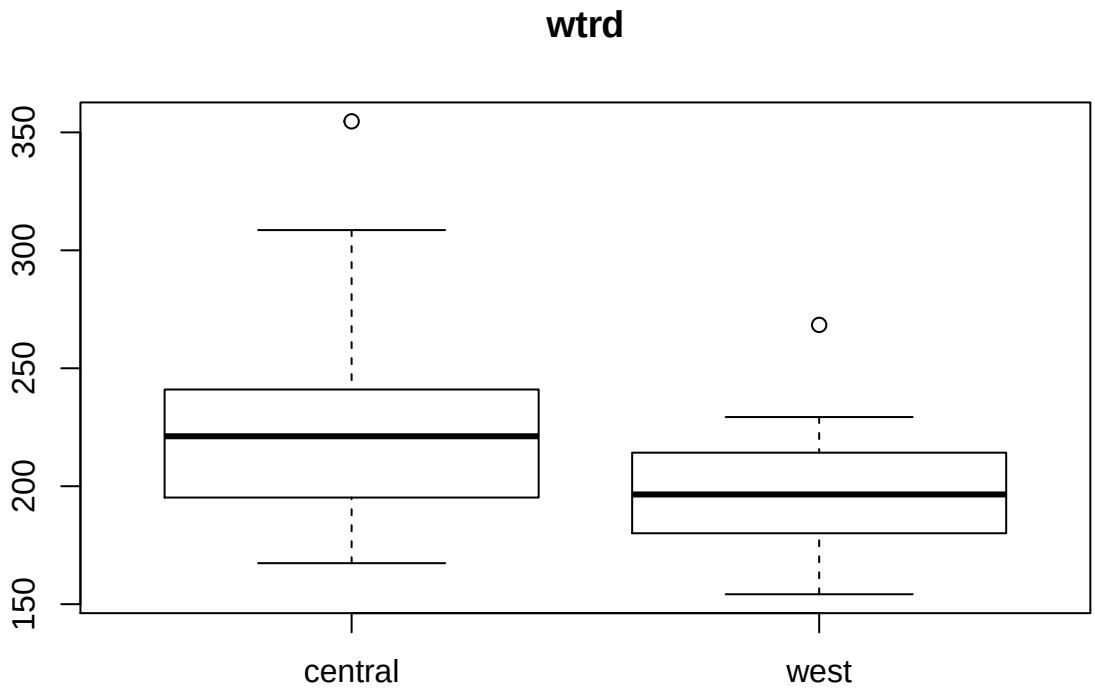

density
0
2
4
6
8
central
west

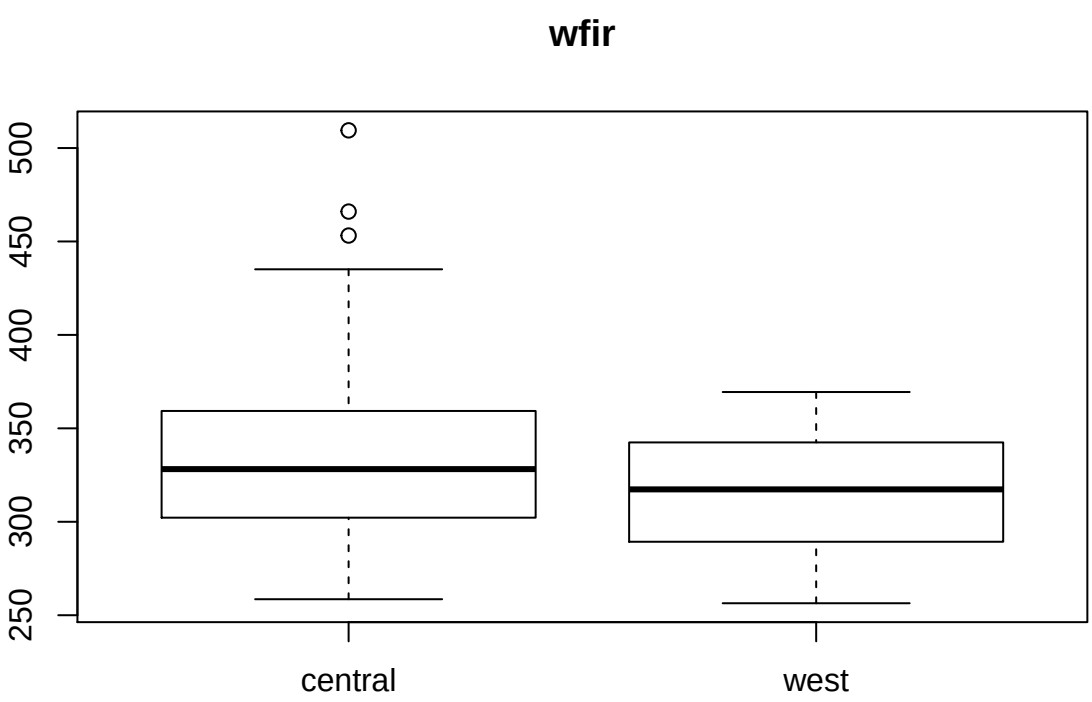

taxpc
70
60
50
40
30
central
west

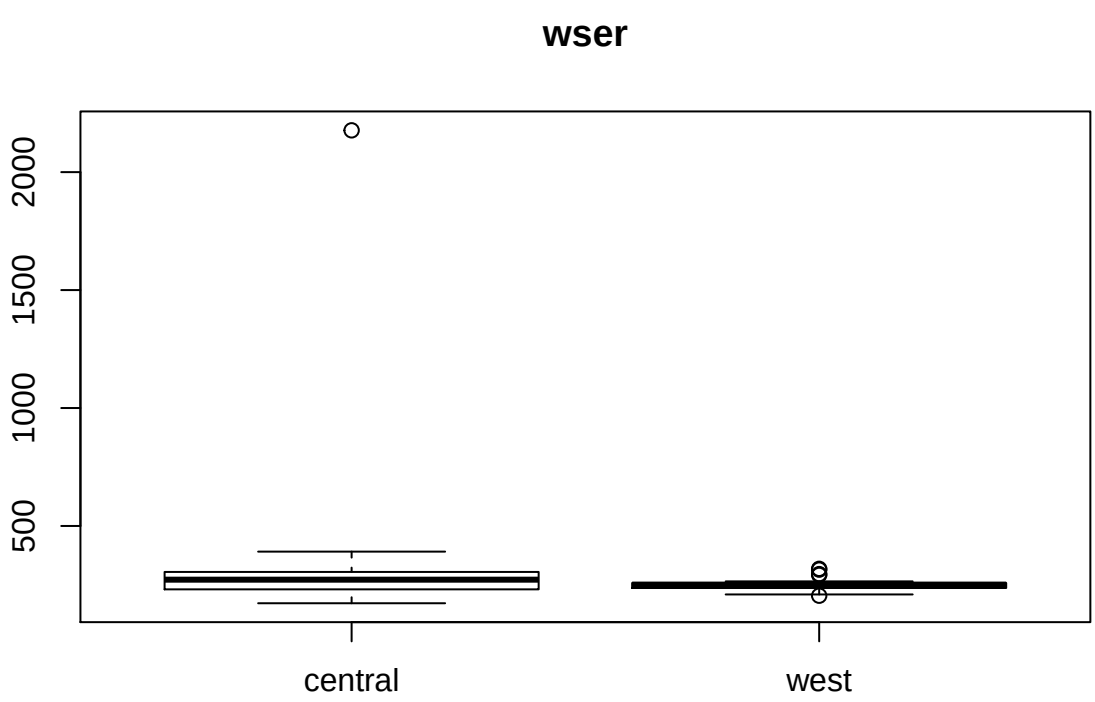

pctmin80
0
10
20
30
40
50
60
central
west

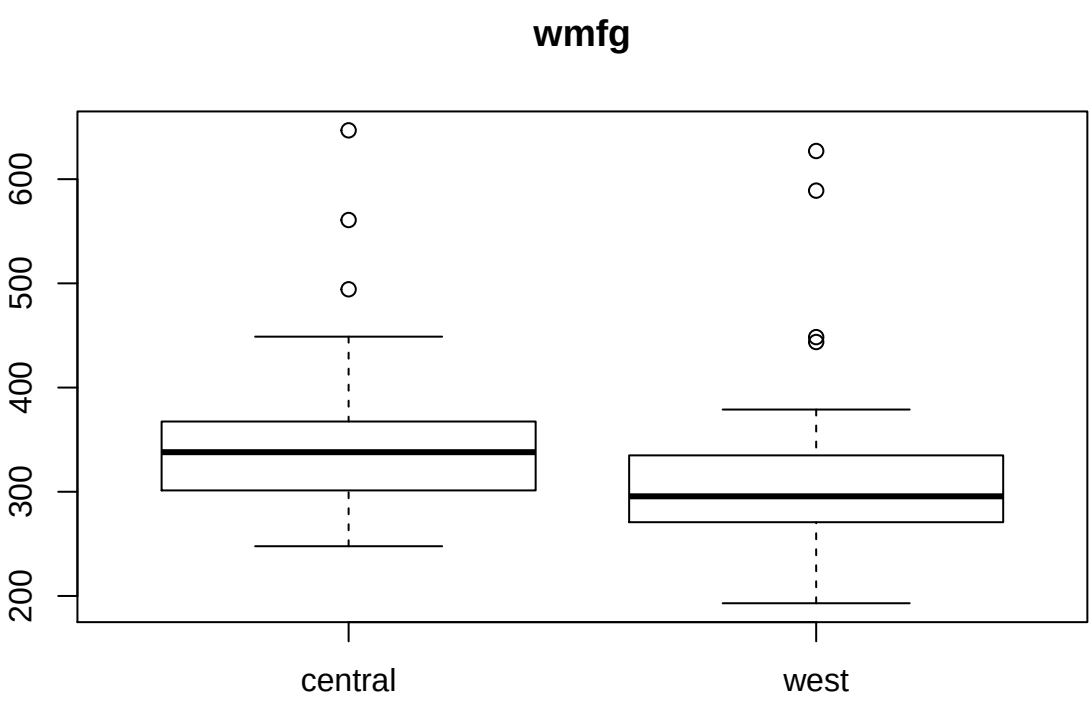

wcon
200
250
300
350
400
central
west

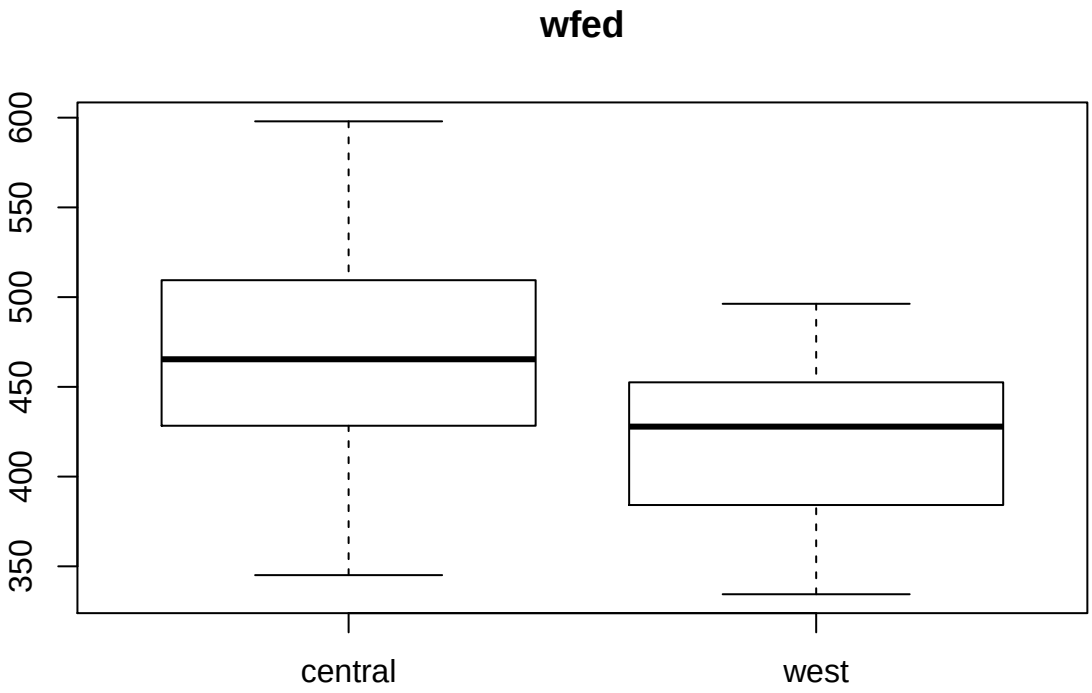

wtuc
600
500
400
300
200
central
west

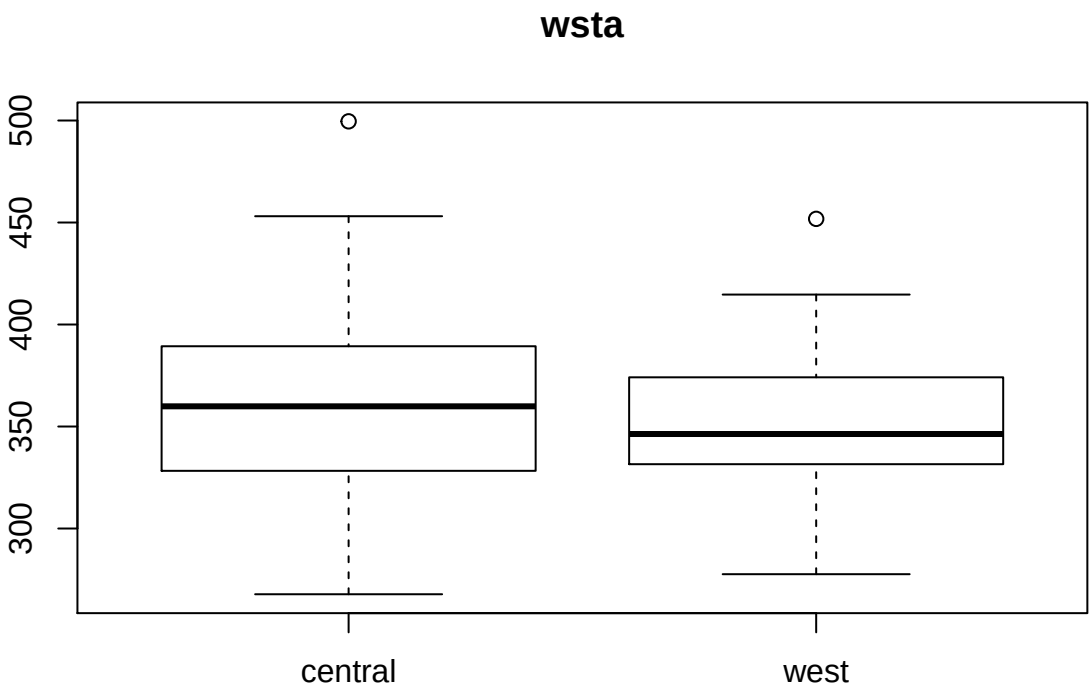

wtrd
350
300
250
200
150
central
west

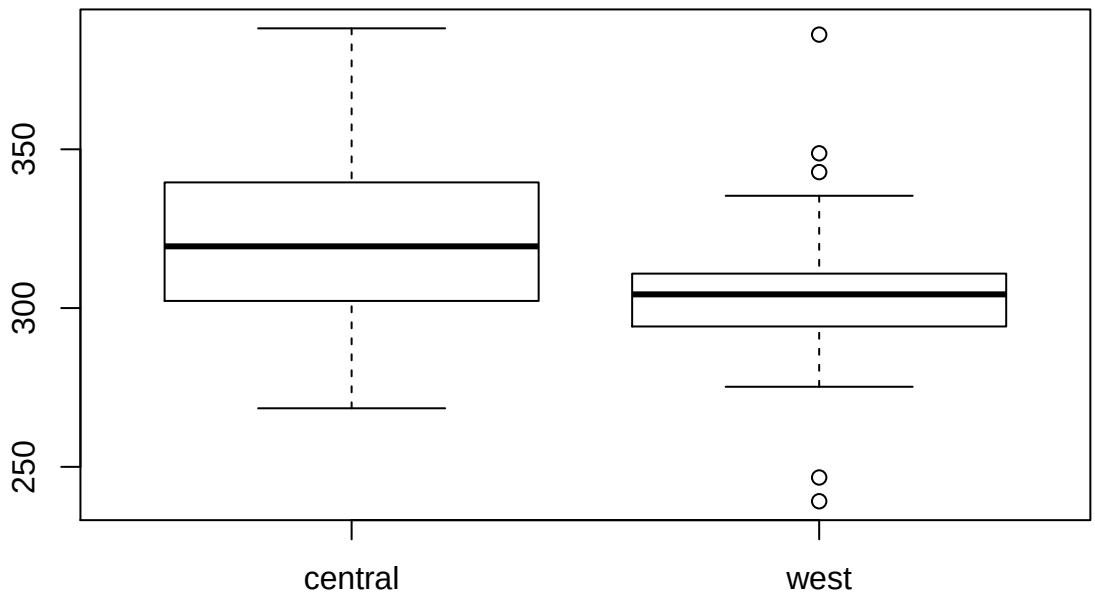

wfir
500
450
400
350
300
250
central
west

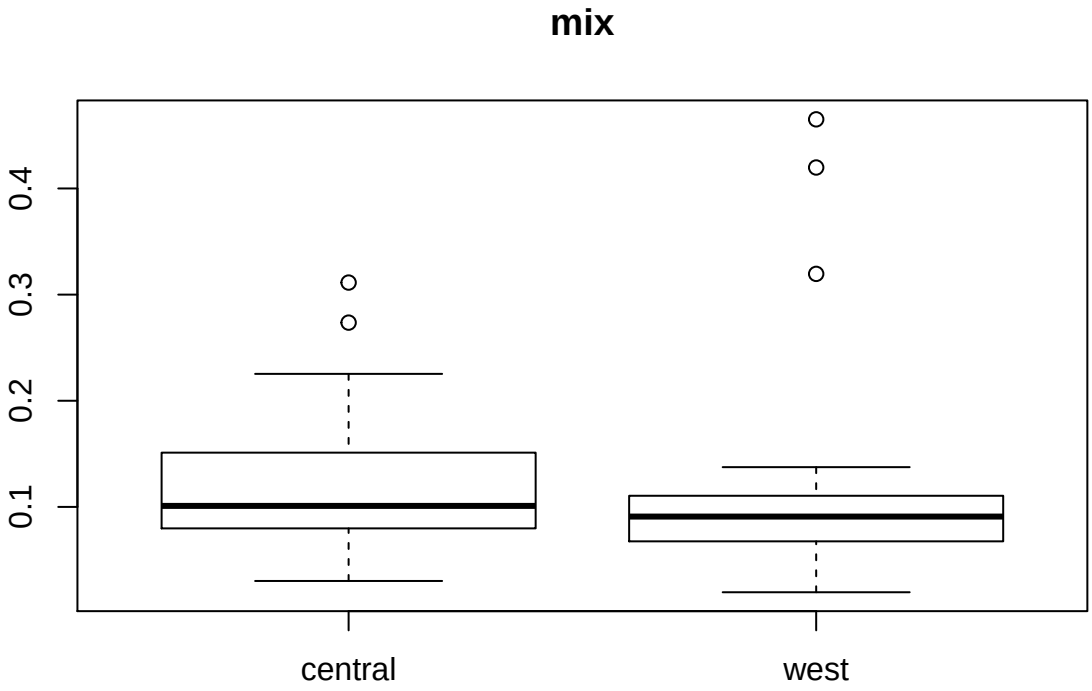

wser
2000
1500
1000
500
central
west

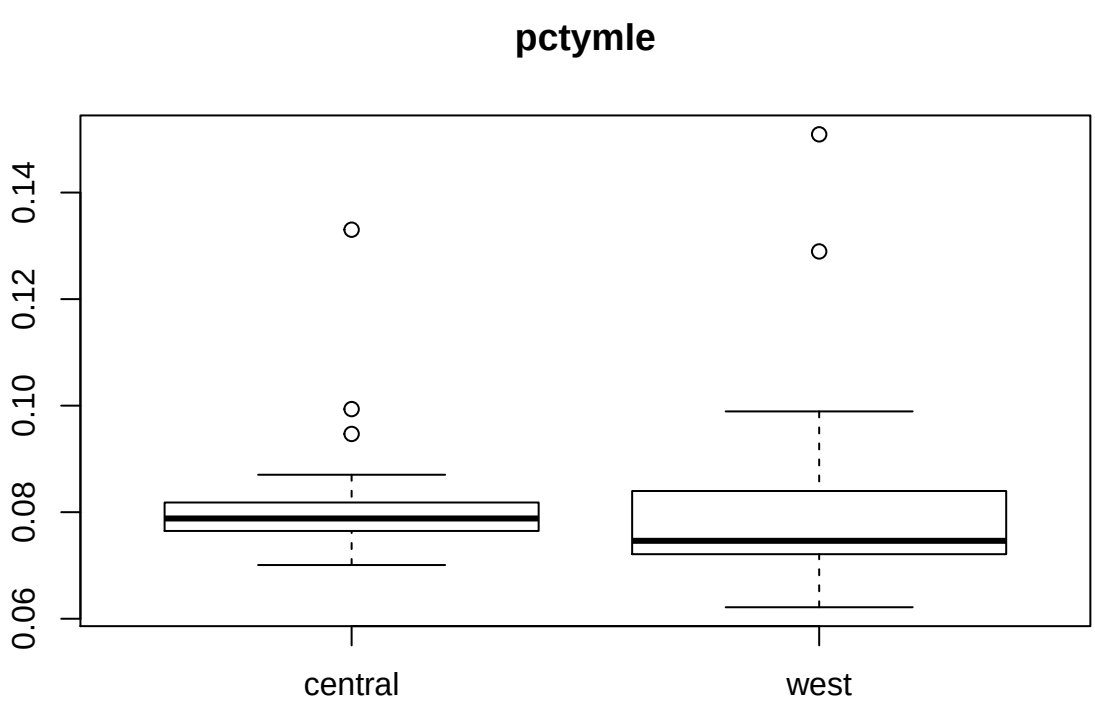

wmfg
200
300
400
500
600
central
west


wfed
600
550
500
450
400
350
central
west


wsta
500
450
400
350
300
central
west


wloc
350
300
250
central
west


mix
0.1
0.2
0.3
0.4
central
west




```
##       crmrte      prbarr      prbconv     prbpris     avgsen
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   0.0989659   1.09091     Numeric,2   0.15        20.7
## group 1           2           Numeric,2   2           2
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       polpc       density     taxpc       pctmin80    wcon
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,3   Numeric,5   Numeric,3   Numeric,2   385.3424
## group Numeric,3   Numeric,5   Numeric,3   Numeric,2   2
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       wtuc        wtrd        wfir        wser        wmfg
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,2   Numeric,2   Numeric,3   Numeric,6   Numeric,7
## group Numeric,2   Numeric,2   Numeric,3   Numeric,6   Numeric,7
## names Character,2 Character,2 Character,2 Character,2 Character,2
##       wfed        wsta        wloc        mix         pctymle
## stats Numeric,10  Numeric,10  Numeric,10  Numeric,10  Numeric,10
## n     Numeric,2   Numeric,2   Numeric,2   Numeric,2   Numeric,2
## conf  Numeric,4   Numeric,4   Numeric,4   Numeric,4   Numeric,4
## out   Numeric,0   Numeric,2   Numeric,5   Numeric,5   Numeric,5
```

```
## group Numeric,0   Numeric,2   Numeric,5   Numeric,5   Numeric,5
## names Character,2 Character,2 Character,2 Character,2 Character,2
```

Comparing central vs west,

central has higher

- crime rate
- density
- tax revenue per capita
- percentage of minority
- percentage of young male
- wages in general are higher except for wtuc

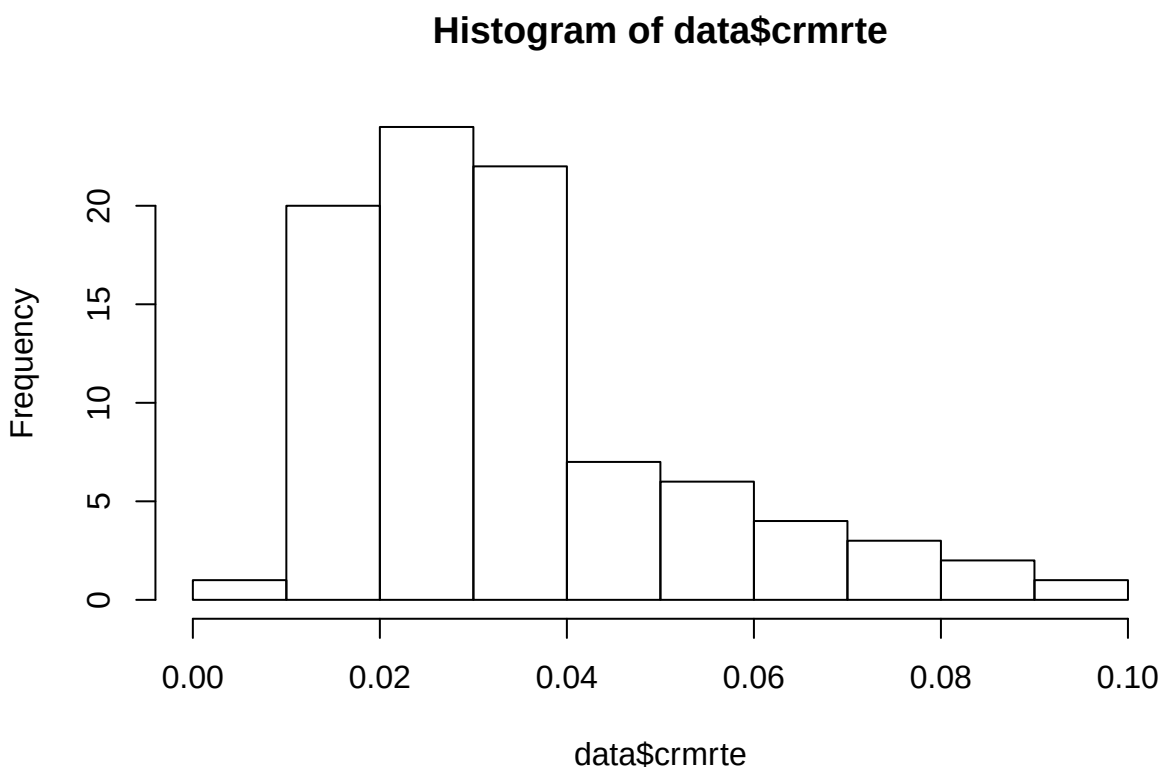
west has higher

- average sentence

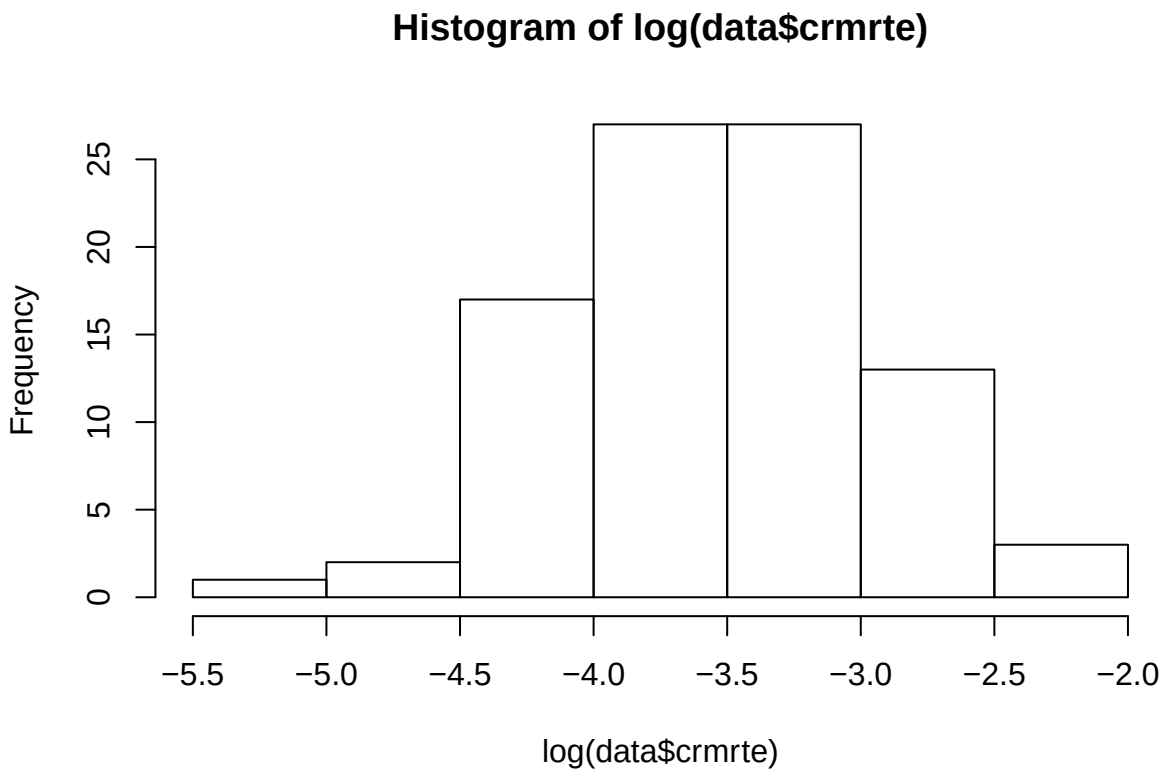
central and west are about the same

- probability of arrest
- probabilitiy of conviction
- probability of prison sentence
- police per capita
- face to face confrontation (central has slightly higher)

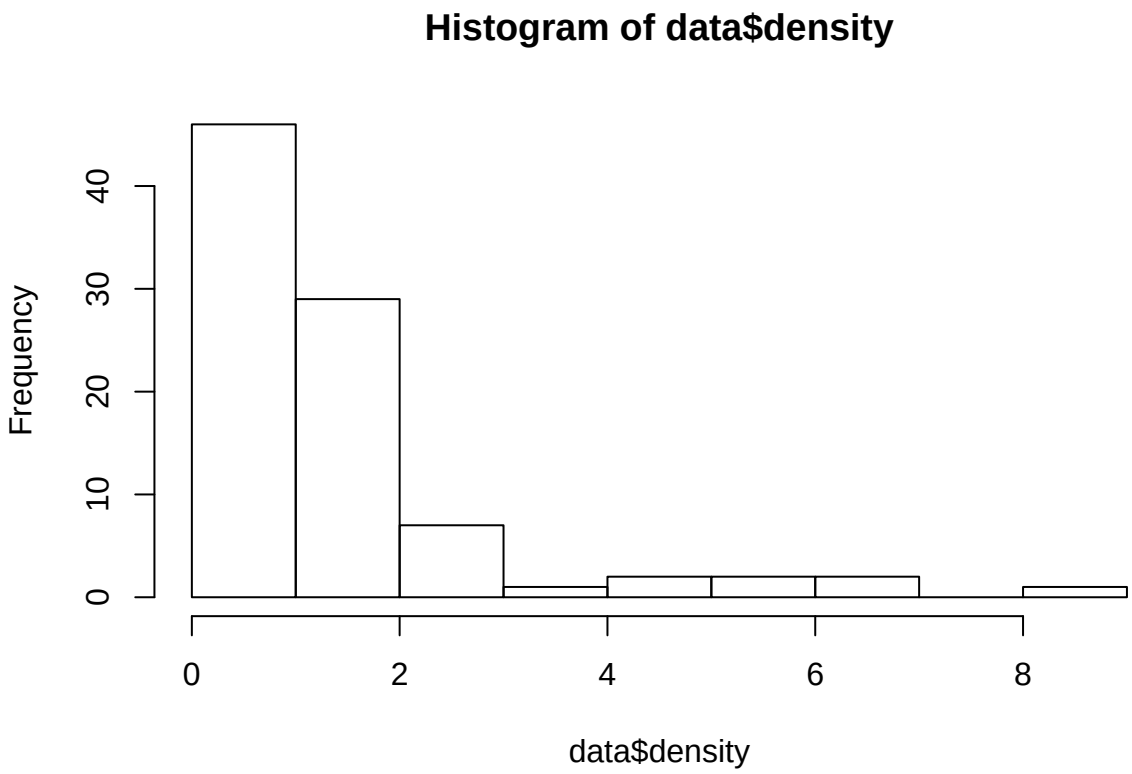
```
# potential dependent variable: crime rate
hist(data$crmrte)
```



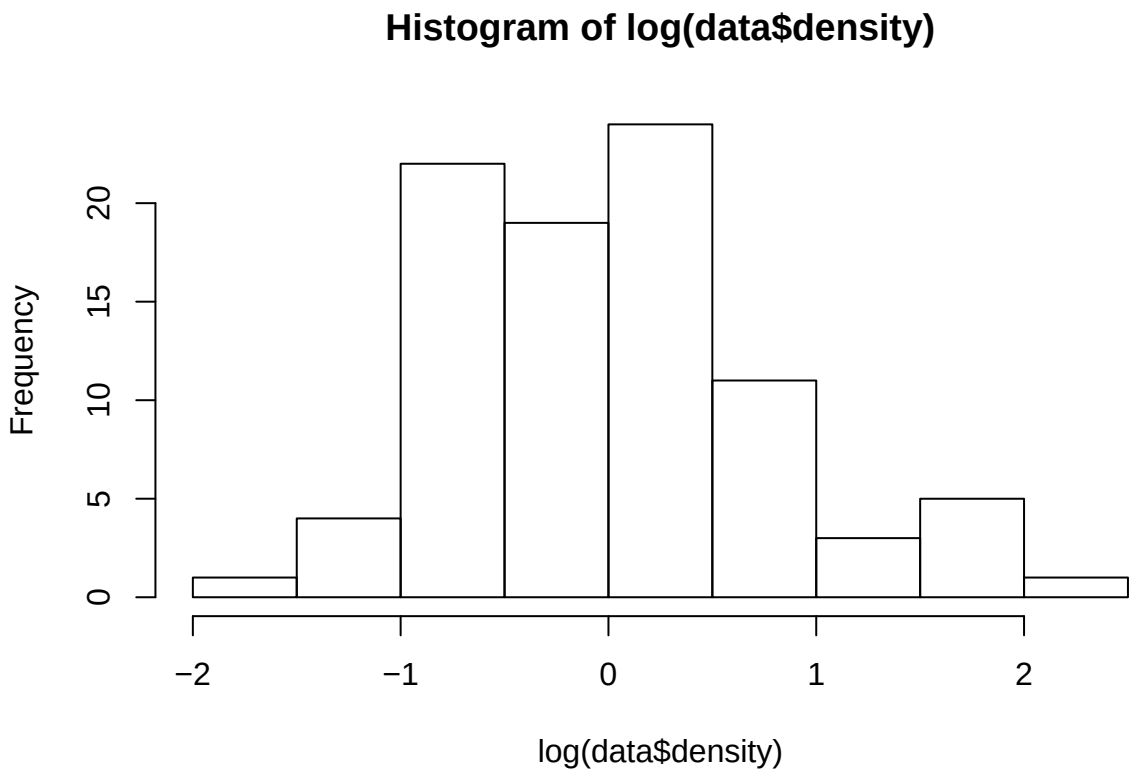

```
hist(log(data$crmrte))
```



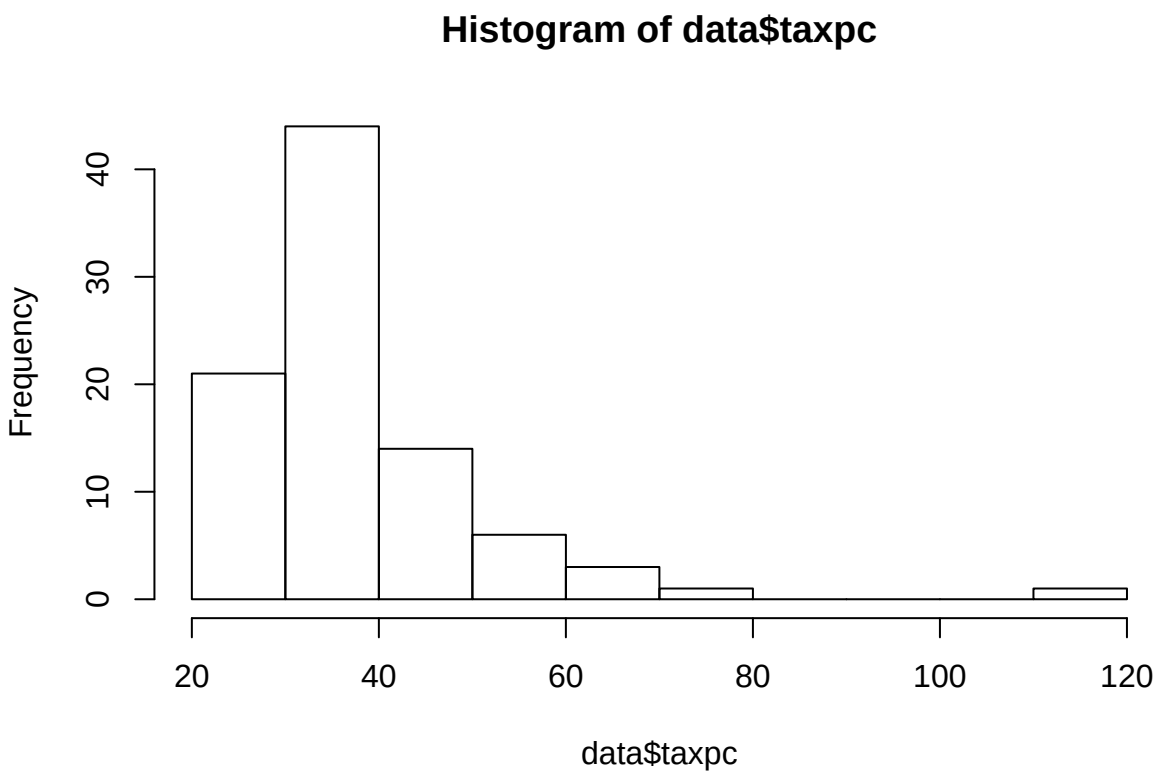

```
# potential independent variables
# 1. density
hist(data$density)
```



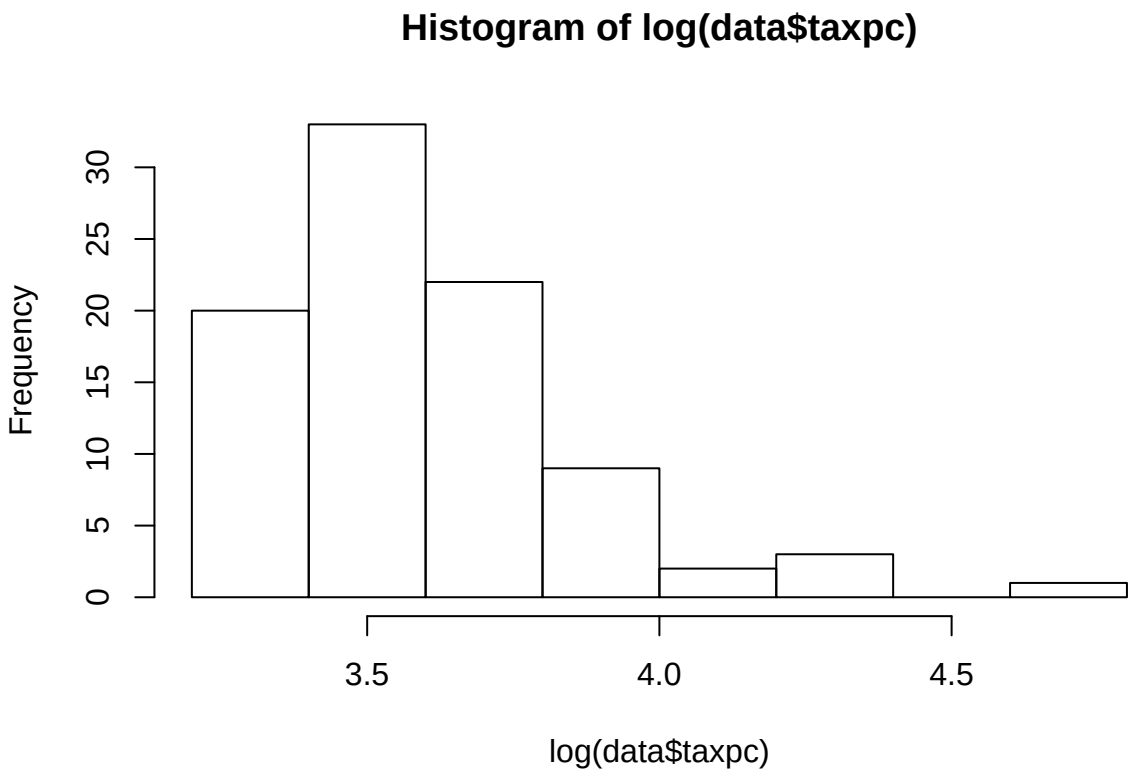

```
hist(log(data$density))
```



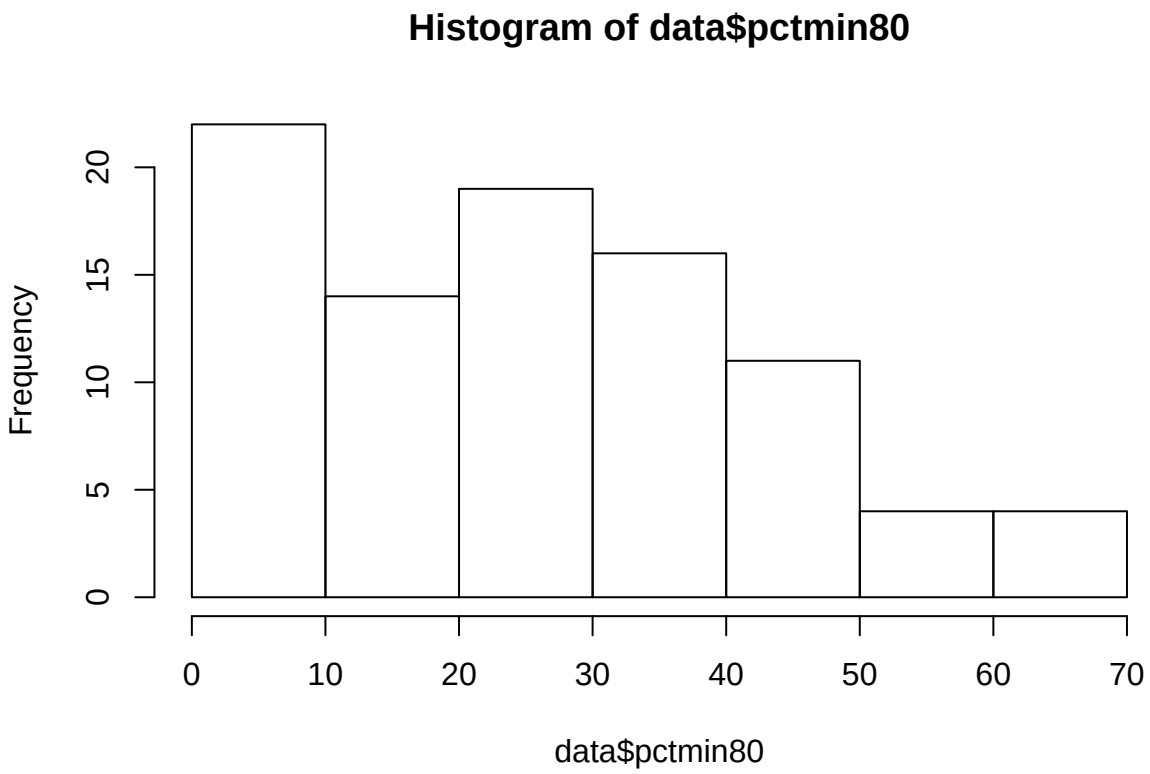

```r
# 2. taxpc
hist(data$taxpc)
```



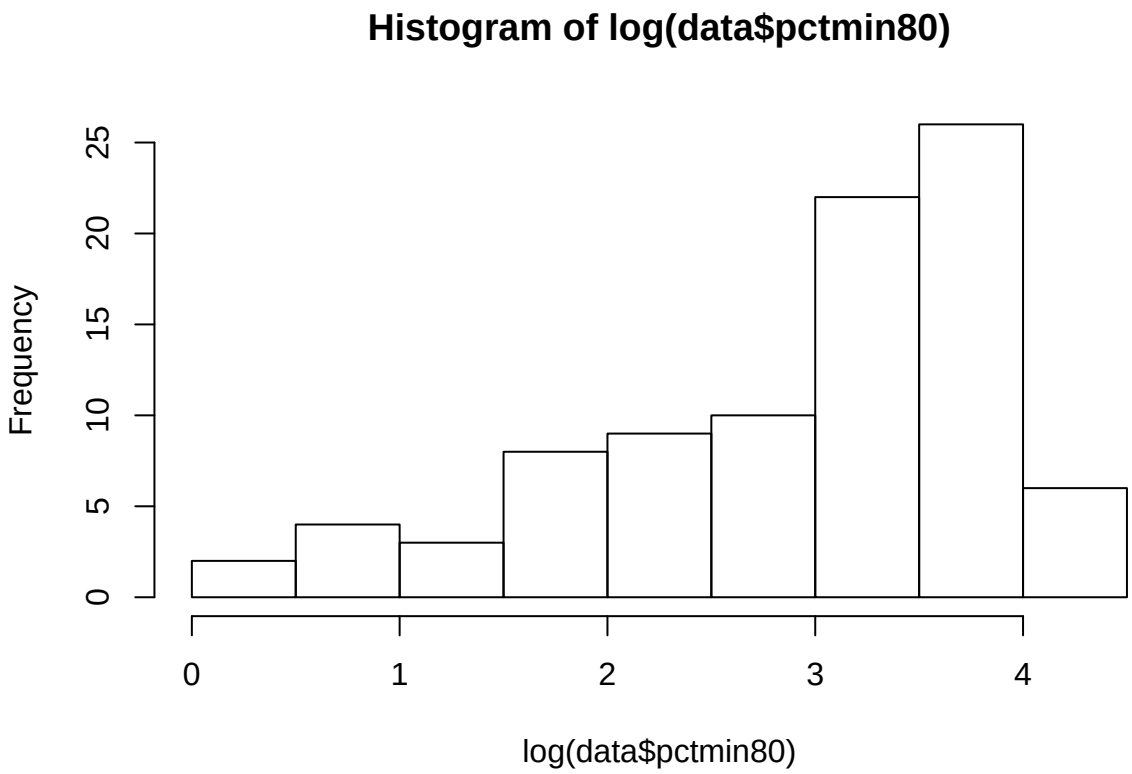

```
hist(log(data$taxpc))
```



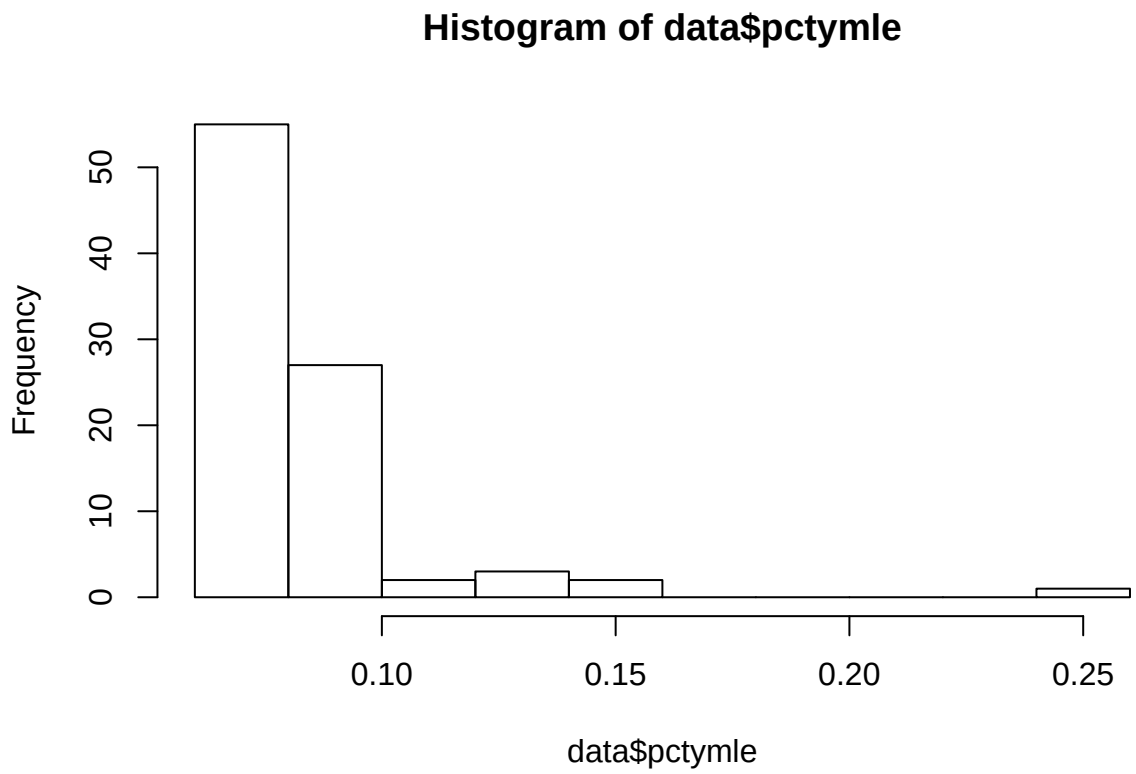

```
# log didn't quite change much because of one outlier
# 3. pctmin80
hist(data$pctmin80)
```



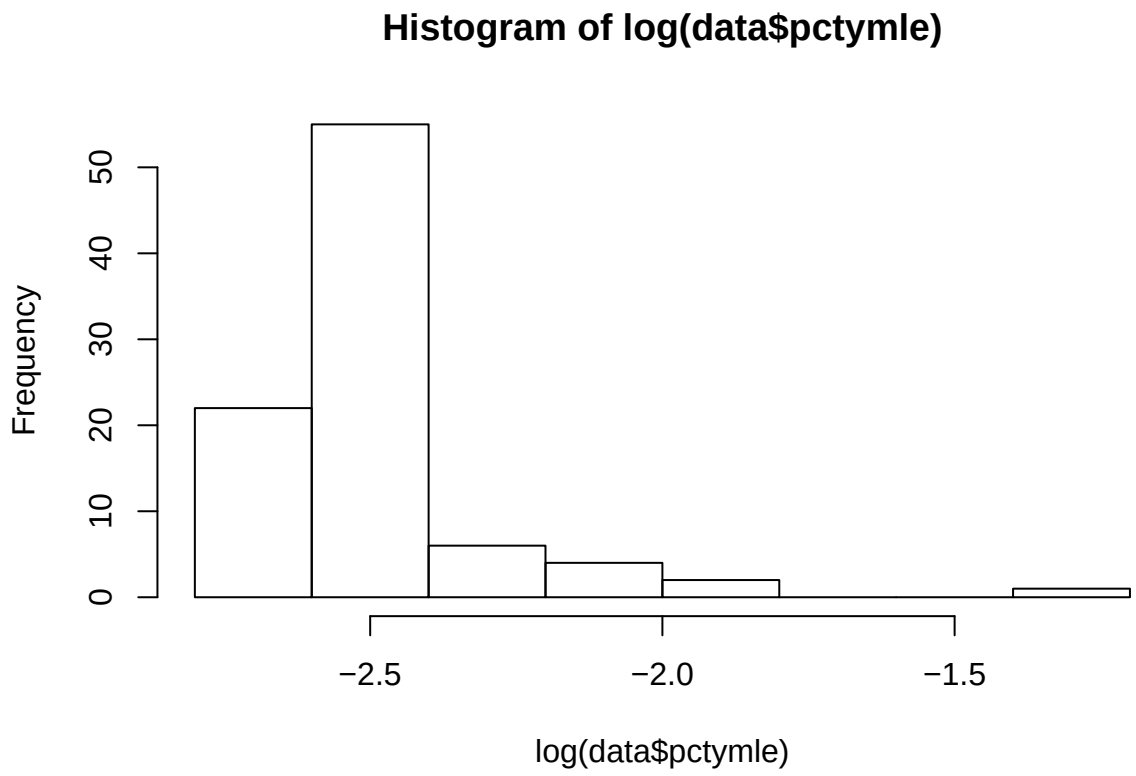

```
hist(log(data$pctmin80))
```



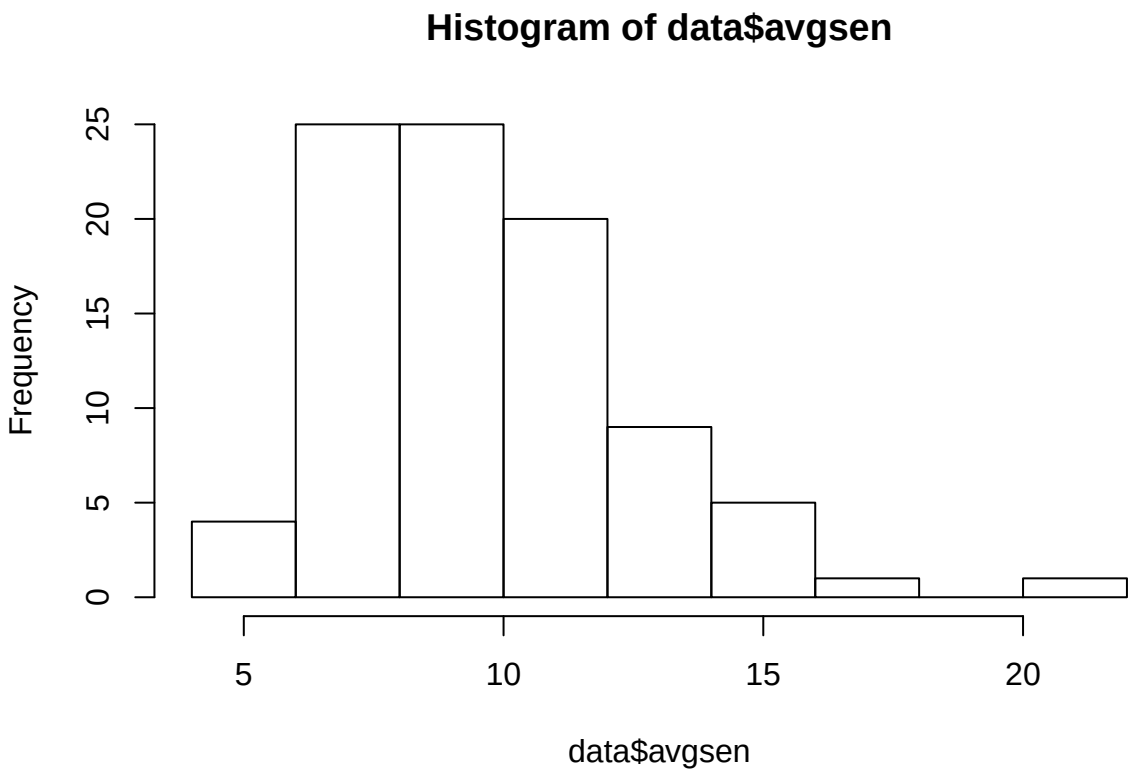

```r
# better leave variable as is because applying a log skewed the distribution
# 4. pctymle
hist(data$pctymle)
```



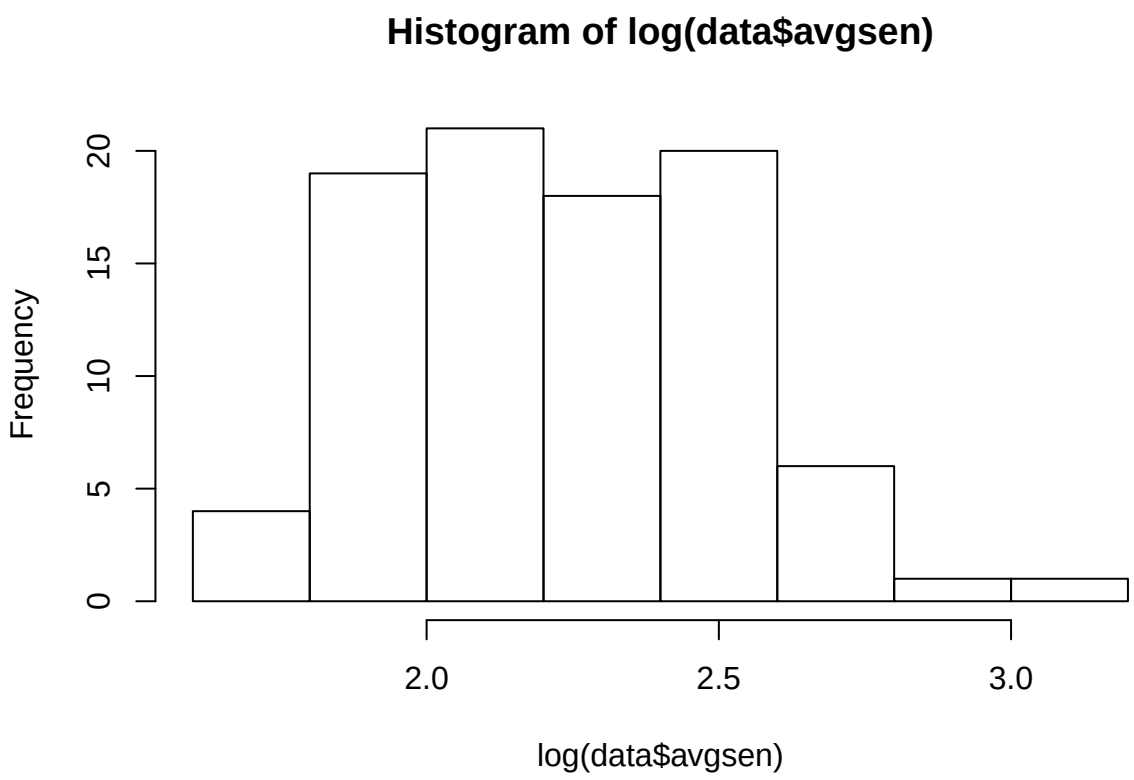

```
hist(log(data$pctymle))
```




```
# log didn't quite change much because of one outlier
# 5. avgsen
hist(data$avgsen)
```




```
hist(log(data$avgsen))
```



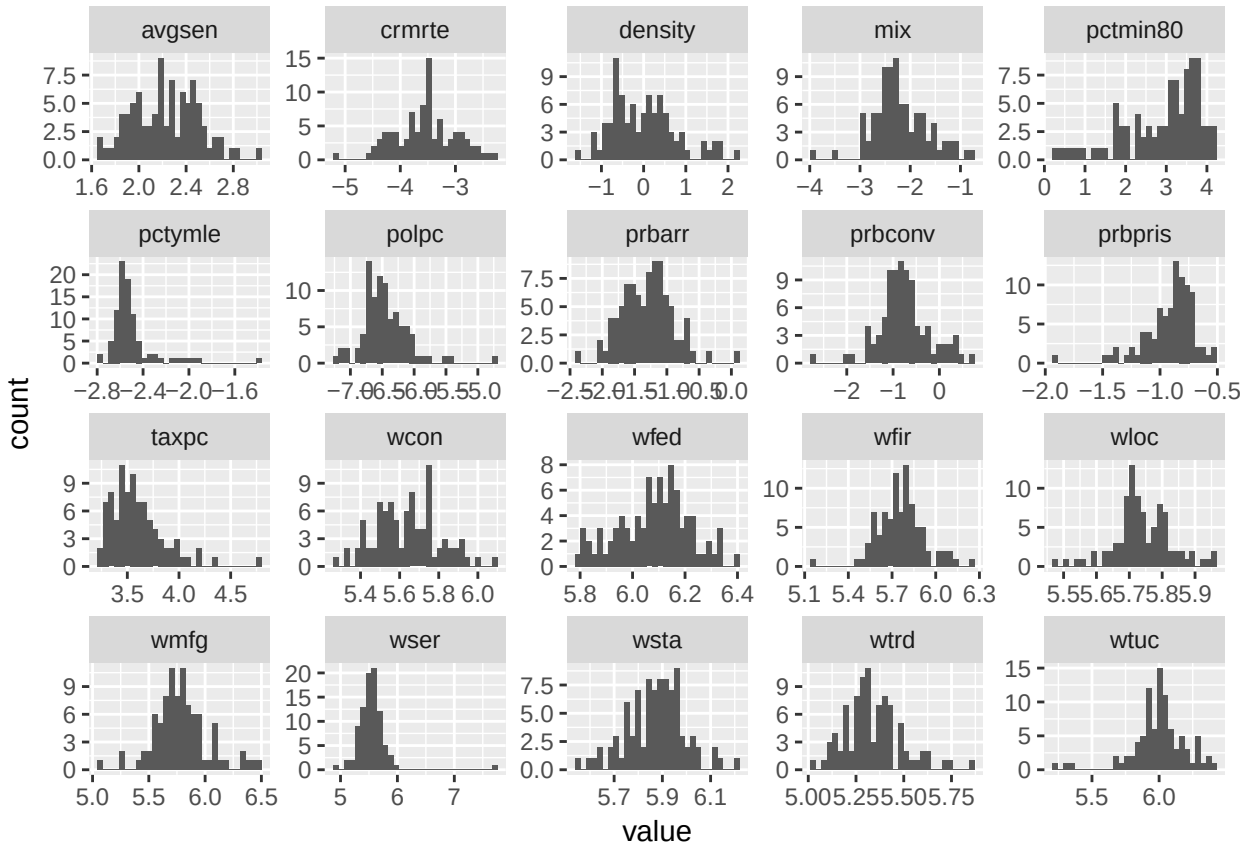

```
# already verified that these variables are not correlated to each other
```

Observations

- All observations were recorded for the year of 1987.
- *urban*, *central*, *west* are categorical variables.
- Most wages variables (wcon, wfed, wfir, wmfg, wser, wsta, wtrd) have a positively skewed distribution which may be due to few number people getting paid above the average.
- wtuc, wloc appear to be normally distributed.
- prbarr, prbconv appear to be positively skewed while prbpris is more negatively skewed.
- avgsen appears to be positively skewed.
- crmrte, density, polpc, prbconv: The histogram indicates that these variables have positive skews. Given the variables have a meaningful zero-point, we can take the log for a more normal distribution.

```
# taking the log of the data excluding x, county, year and categorical variables
plot.log.data <- log(data[!(names(data) %in% c("X", "county", "year", "urban", "central", "west"))])
ggplot(gather(plot.log.data), aes(value)) +
       facet_wrap(~key, scales="free") +
       geom_histogram()
```

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



Observations after taking logs: It looks like the log transformation of variables cmrte, mix, prbconv, wfed, wfir, wmfg, and wsta have made the distributions quite normal. This will help ensure the errors of the model are normal.

Proposed Model Based on the exploratory data analysis and general intution about the potential determinants of crime, an initial proposed model specification and coefficient expectation are:

- Sum of all wages: Summing the wage variables across sectors may identify whether income inequality between counties may explain the difference in crime rates. Initial thoughts are that sum of wages (higher incomes) lead to lower crime rates, so a linear relationship between sum of wages and crimes committed per person is expected with a negative coefficient.
- log(prbarr) Probability of arrest: There is the possibility that the probability of arrest is positively correlated with crime rate, as higher numbers of arrest can increase the number of crimes recorded.
- tax revenue per capita (taxpc): Lack of government-funded resources can take the form of a lack of educational opportunities or employment options, thus leading to rise in crime rates.

Model 1: $log(crmrte) = \beta_0 + \beta_1(allwages) + \beta_2 log(prbarr) + \beta_3(taxrev) + u$

Model Building Process

TODO: A model building process, supported by exploratory analysis. Your EDA should be interspersed with, and support, your modeling decisions. In particular, you should use exploratory techniques to address * What transformations to apply to variables and what new variables should be created. * What variables should be included in each model * Whether model assumptions are met

$density [1] "8 : 3.93455100059509, 4.38875865936279, 4.8347339630127, 5.12442398071289, 5.6744966506958, 6.28648662567139, 6.42718458175659, 8.82765197753906"

$taxpc [1] "6 : 56.8621063232422, 61.1525115966797, 67.6796340942383, 67.8479766845703, 75.6724319458008, 119.761451721191"

Model Specifications

Model 1

TODO: * One model with only the explanatory variables of key interest (possibly transformed, as determined by your EDA), and no other covariates.

$log(crmrte) = \beta_0 + \beta_1 \cdot log(density) + \beta_2 \cdot (taxpc) + u$

```
m1 <- lm(log(crmrte) ~ log(density) + taxpc, data=data)
```

TODO: For your first model, a detailed assessment of the 6 CLM assumptions. For additional models, you should check all assumptions, but only highlight major differences from your first model in your report.

CLM 1 - A linear model

The model is specified such that the dependent variable is a linear function of the explanatory variables. Is the assumption valid? *Yes*

Response: No response required.

CLM 2 - Random Sampling

TODO

CLM 3 - Multicollinearity

```
# show correlation
data$log.density <- log(data$density)
cor(data.matrix(subset(data, select=c("density", "log.density", "taxpc"))))
```

```
##                density log.density     taxpc
## density     1.0000000   0.8896747 0.3204737
## log.density 0.8896747   1.0000000 0.1841222
## taxpc       0.3204737   0.1841222 1.0000000
```

```
# show vif
vif(m1)
```

```
## log(density)        taxpc
##     1.035091     1.035091
```

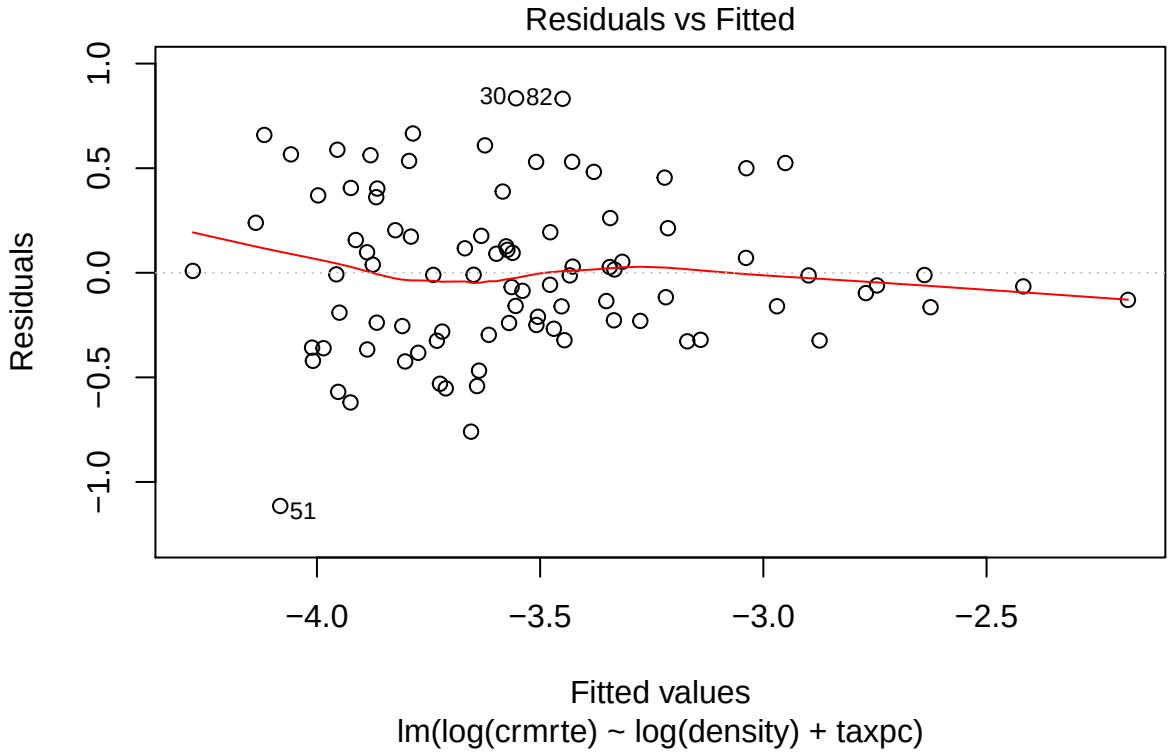
The two explanatory variables (log.density and taxpc) are not perfectly correlated and the VIFs are low (less than 4), so there is no perfect multicollinearity of the independent variables.

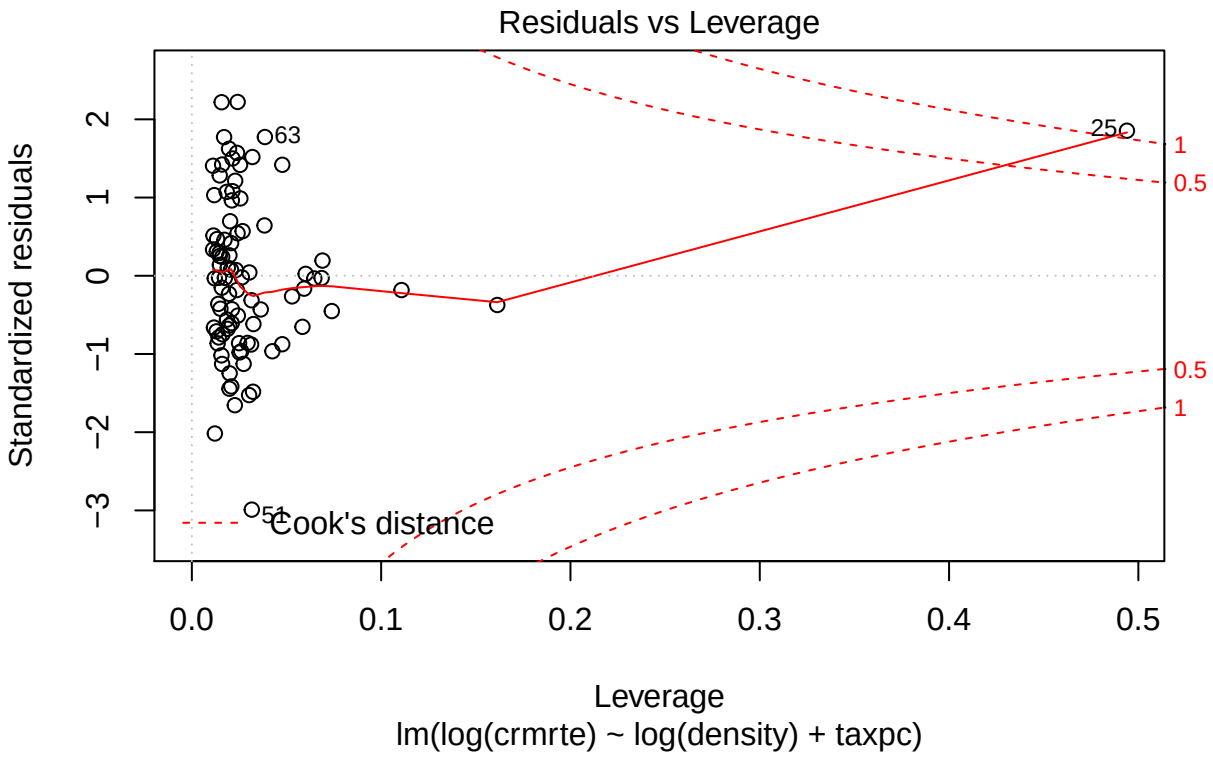
Is the assumption valid? *Yes*

Response: No response required.

CLM 4 - Zero-Conditional Mean

```
plot(m1, which=c(1, 5))
```






```
# exogenous check
cov(log(data$density), m1$residuals)
```

```
## [1] -8.896016e-18
```

```
cov(data$taxpc, m1$residuals)
```

```
## [1] -4.453513e-16
```

The covariances of the two independent variables with the residuals are very close to zero indicating they are likely exogenous.

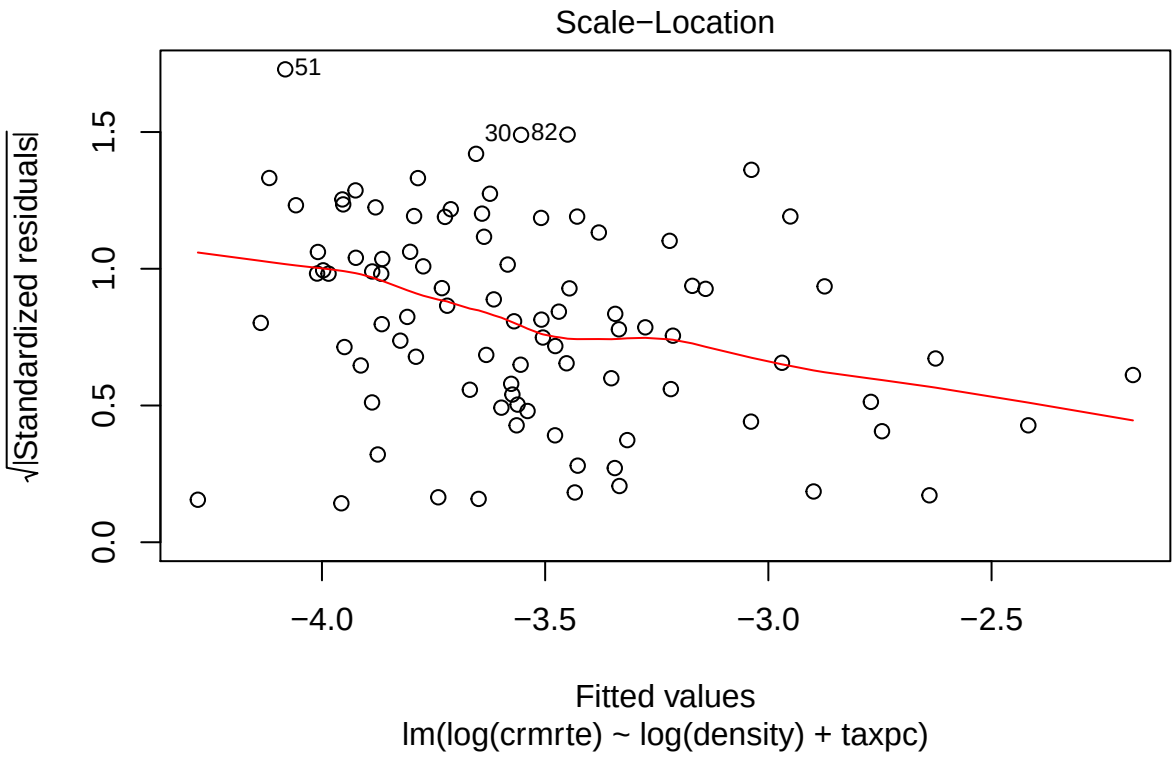
There is a data point with a large Cook's distance.

Is the assumption valid?

Response:

CLM 5 - Homoscedasticity

```
# spreadLevelPlot(m1)
plot(m1, which=3)
```




```
bptest(m1)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  m1
## BP = 7.2256, df = 2, p-value = 0.02698
```

not significant p-value for Breusch-Pagan test -> assumption of homoscedasticity met

```
ncvTest(m1)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 6.968285    Df = 1     p = 0.008296697
```

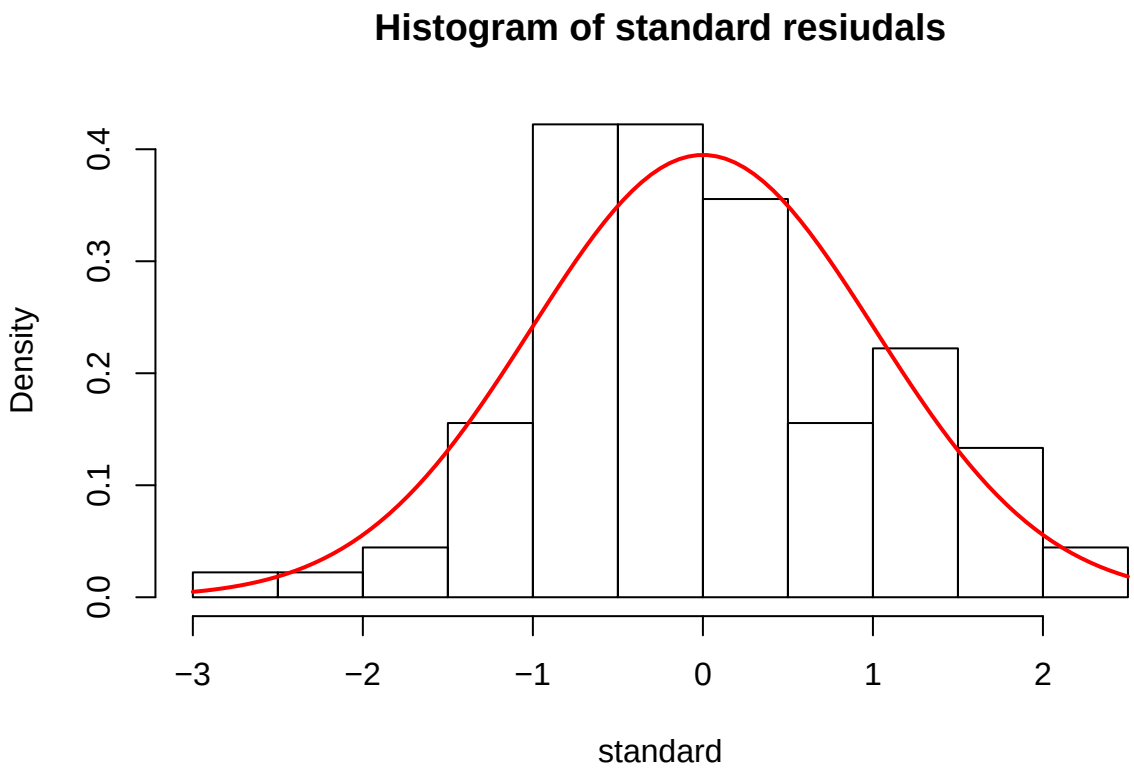
significant p-value for Score Test -> assumption of homoscedasticity met

Is the assumption valid? *Yes*

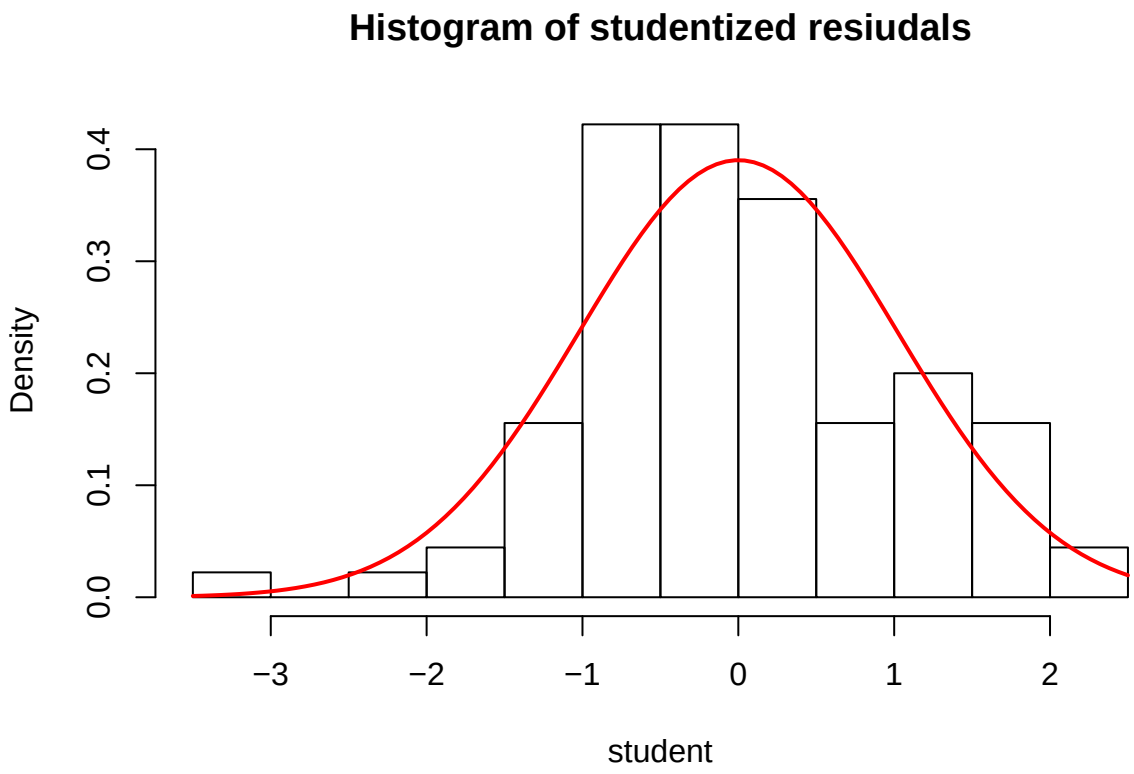
Response:

CLM 6 - Normality of residuals

```
# normality of standard residuals
standard <- rstandard(m1)
hist(standard, main="Histogram of standard resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(standard)), col="red", lwd=2, add=TRUE)
```

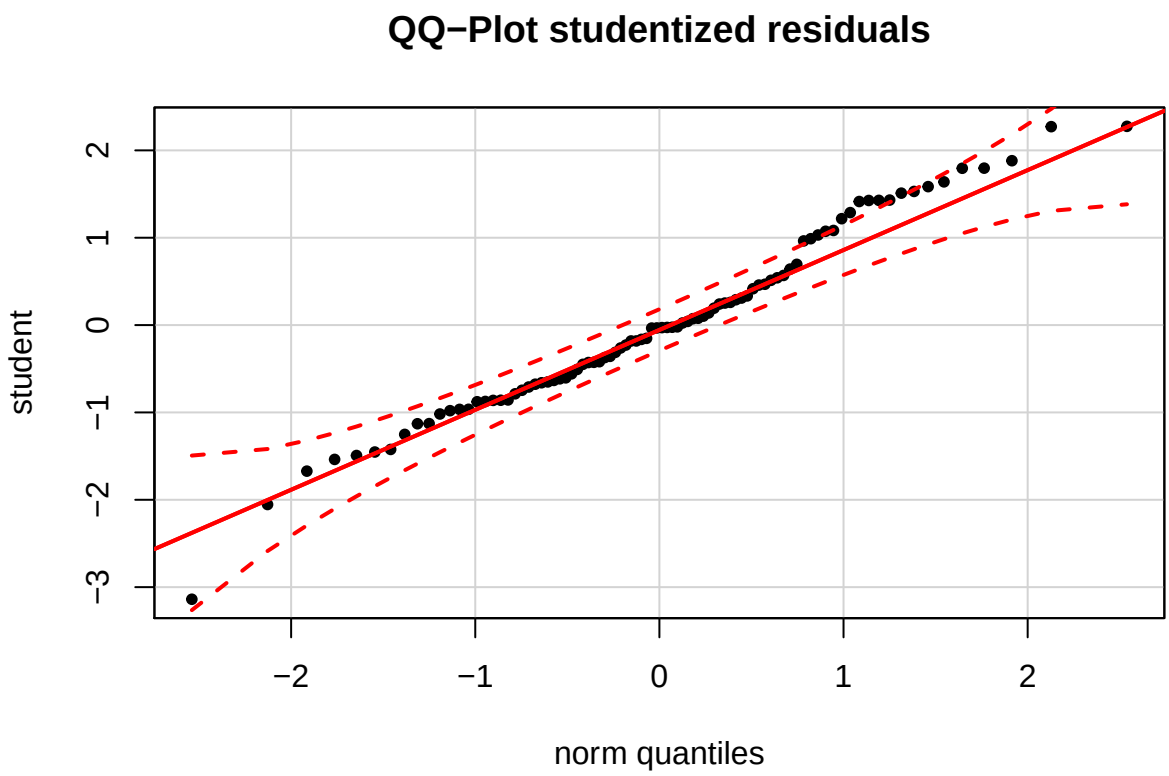



```
# normality of studentized residuals
student <- rstudent(m1)
hist(student, main="Histogram of studentized resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(student)), col="red", lwd=2, add=TRUE)
```




```r
# QQ plot standard residuals
qqPlot(standard, distribution="norm", pch=20, main="QQ-Plot standard residuals")
qqline(standard, col="red", lwd=2)
```

```r
# QQ plot studentized residuals
qqPlot(student, distribution="norm", pch=20, main="QQ-Plot studentized residuals")
qqline(student, col="red", lwd=2)
```



The histograms in particular appear to be fairly normally distributed, while the Q-Q plot doesn't deviate significantly from normality either, so overall the residuals appear to be fairly normal. Notably the log transformation of views has helped to produce normal errors.

Is the assumption valid? *Yes*

Response: *No response required.*

TODO: * One model that includes key explanatory variables and only covariates that you believe increase the accuracy of your results without introducing bias (for example, you should not include outcome variables that will absorb some of the causal effect you are interested in). This model should strike a balance between accuracy and parsimony and reflect your best understanding of the determinants of crime.

```
m2 <- lm(log(crmrte) ~ log(density) + taxpc + urban, data=data)
```

CLM 1 - A linear model

The model is specified such that the dependent variable is a linear function of the explanatory variables. Is the assumption valid? *Yes*

Response: No response required.

CLM 2 - Random Sampling

TODO

CLM 3 - Multicollinearity

```
# show correlation
data$log.density <- log(data$density)
cor(data.matrix(subset(data, select=c("density", "log.density", "taxpc", "urban"))))
```

```
##                density log.density     taxpc     urban
## density     1.0000000   0.8896747 0.3204737 0.8206825
## log.density 0.8896747   1.0000000 0.1841222 0.6490078
## taxpc       0.3204737   0.1841222 1.0000000 0.3457462
## urban       0.8206825   0.6490078 0.3457462 1.0000000
```

```
# show vif
vif(m2)
```

```
## log(density)        taxpc        urban
##     1.733261     1.139396     1.901850
```

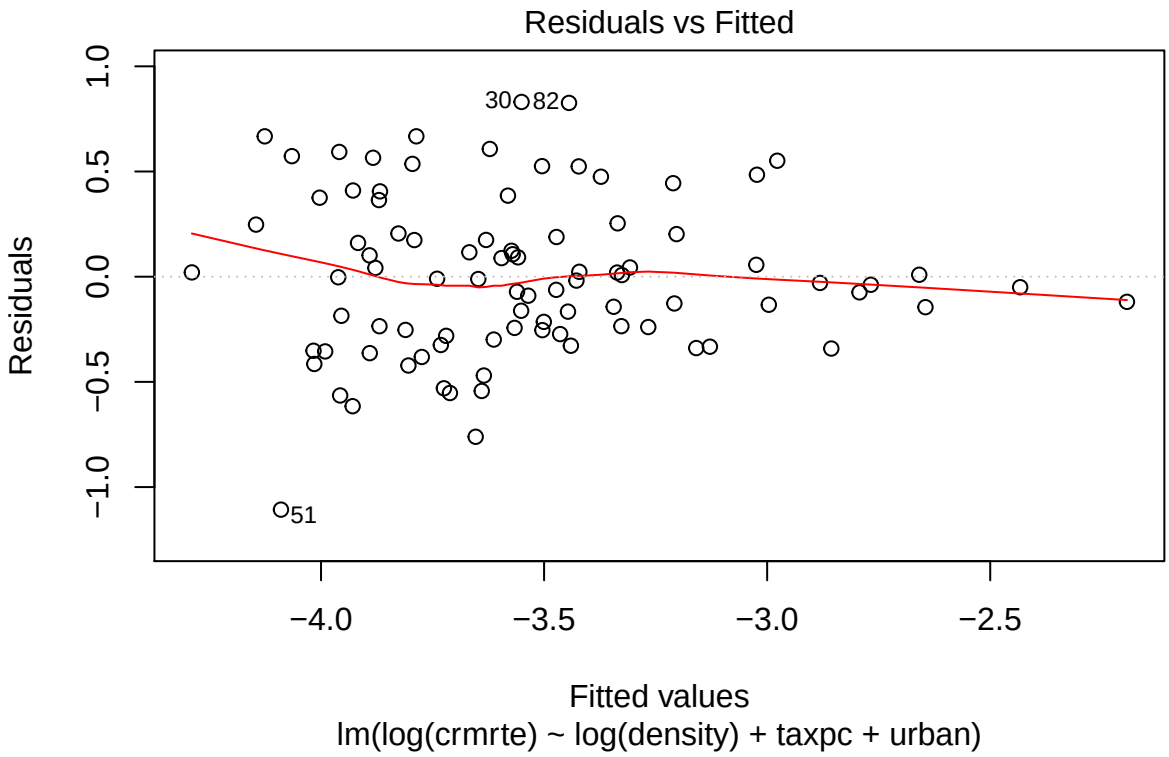
The two explanatory variables (log.density and taxpc) are not perfectly correlated and the VIFs are low (less than 4), so there is no perfect multicollinearity of the independent variables.

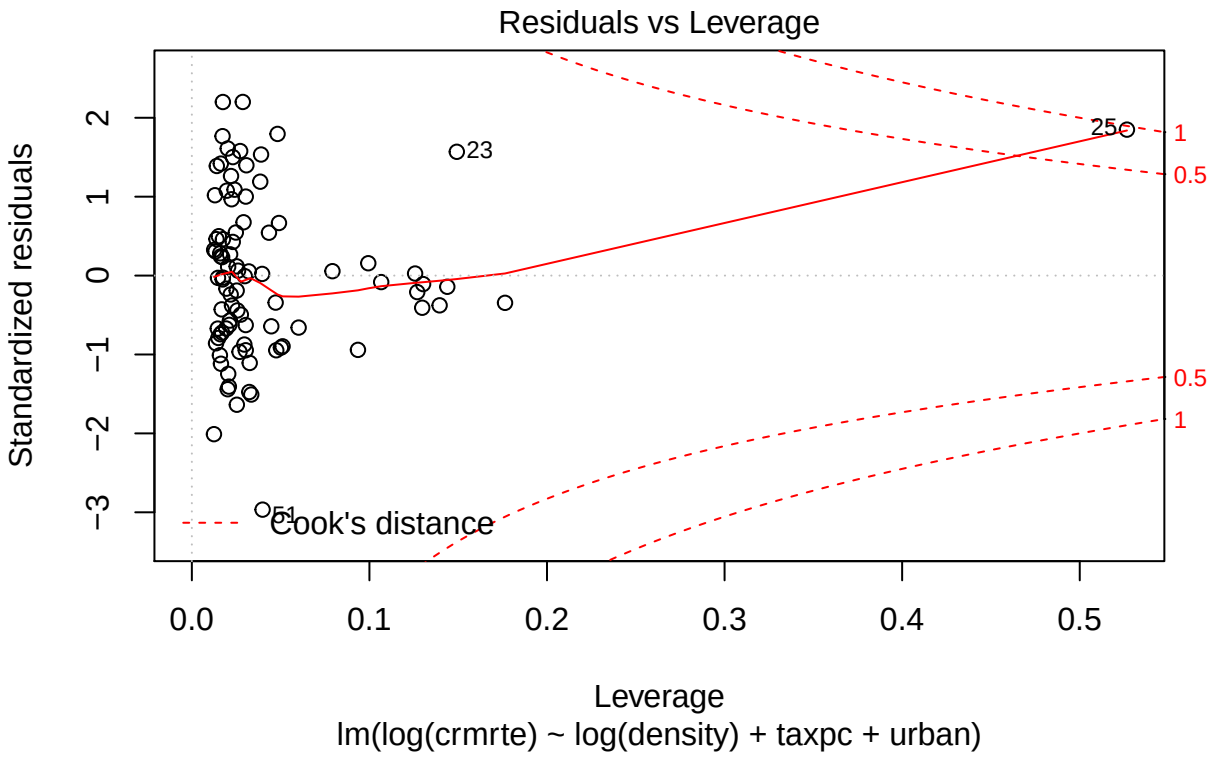
Is the assumption valid? *Yes*

Response: No response required.

CLM 4 - Zero-Conditional Mean

```
plot(m2, which=c(1, 5))
```


Residuals vs Fitted
Residuals
1.0
0.5
0.0
−0.5
−1.0
30
82
51
−4.0
−3.5
−3.0
−2.5
Fitted values
lm(log(crmrte) ~ log(density) + taxpc + urban)




```
# exogenous check
cov(log(data$density), m2$residuals)
```

```
## [1] -8.492333e-18
```

```
cov(data$taxpc, m2$residuals)
```

```
## [1] -3.523097e-16
```

```
# TODO: figure out what to do with covariate
cov(data$urban, m2$residuals)
```

```
## [1] 9.501997e-19
```

The covariances of the two independent variables with the residuals are very close to zero indicating they are likely exogenous.

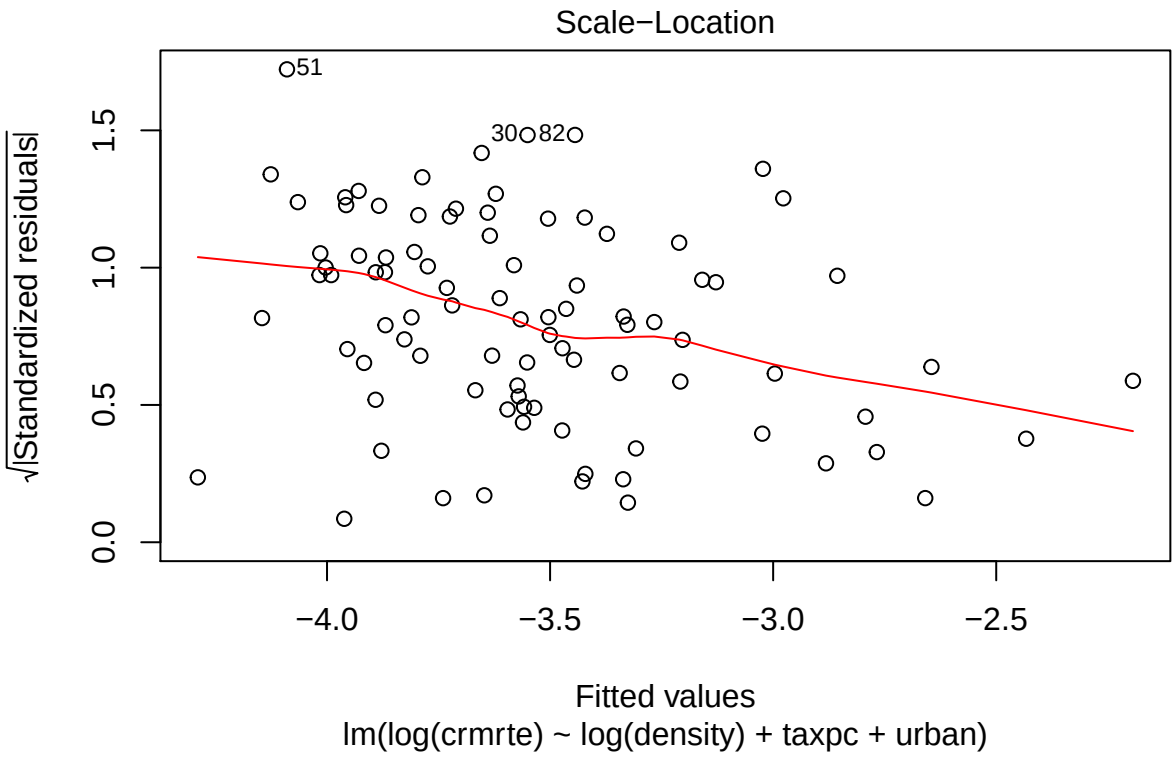
There is a data point with a large Cook's distance.

Is the assumption valid?

Response:

CLM 5 - Homoscedasticity

```
# spreadLevelPlot(m1)
plot(m2, which=3)
```




```
bptest(m2)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  m2
## BP = 7.708, df = 3, p-value = 0.05245
```

not significant p-value for Breusch-Pagan test -> assumption of homoscedasticity met

```
ncvTest(m2)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 7.064728    Df = 1     p = 0.007861626
```

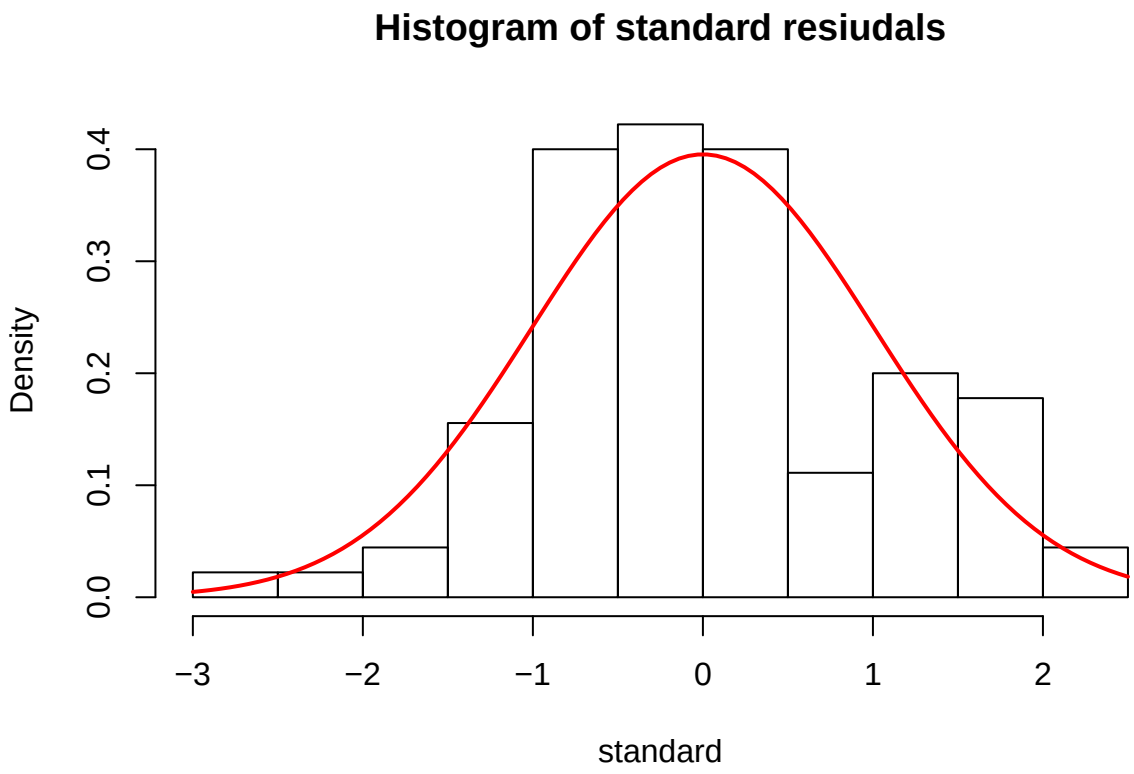
significant p-value for Score Test -> assumption of homoscedasticity met

Is the assumption valid? *Yes*

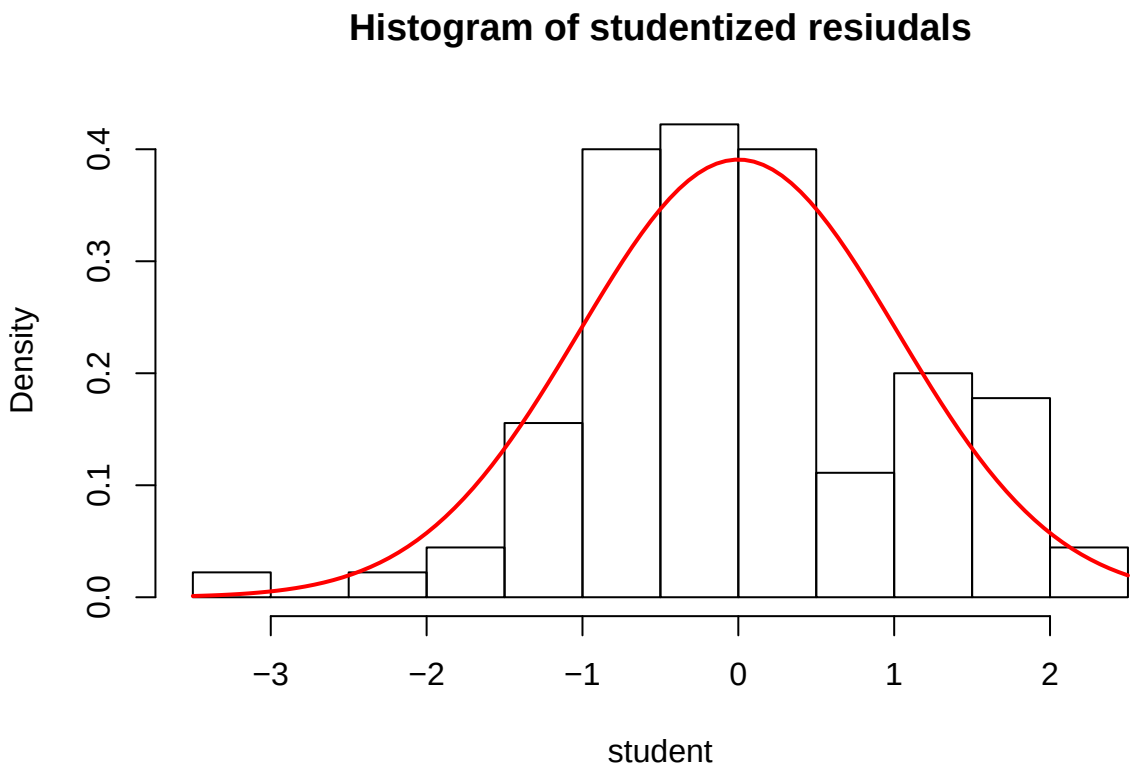
Response:

CLM 6 - Normality of residuals

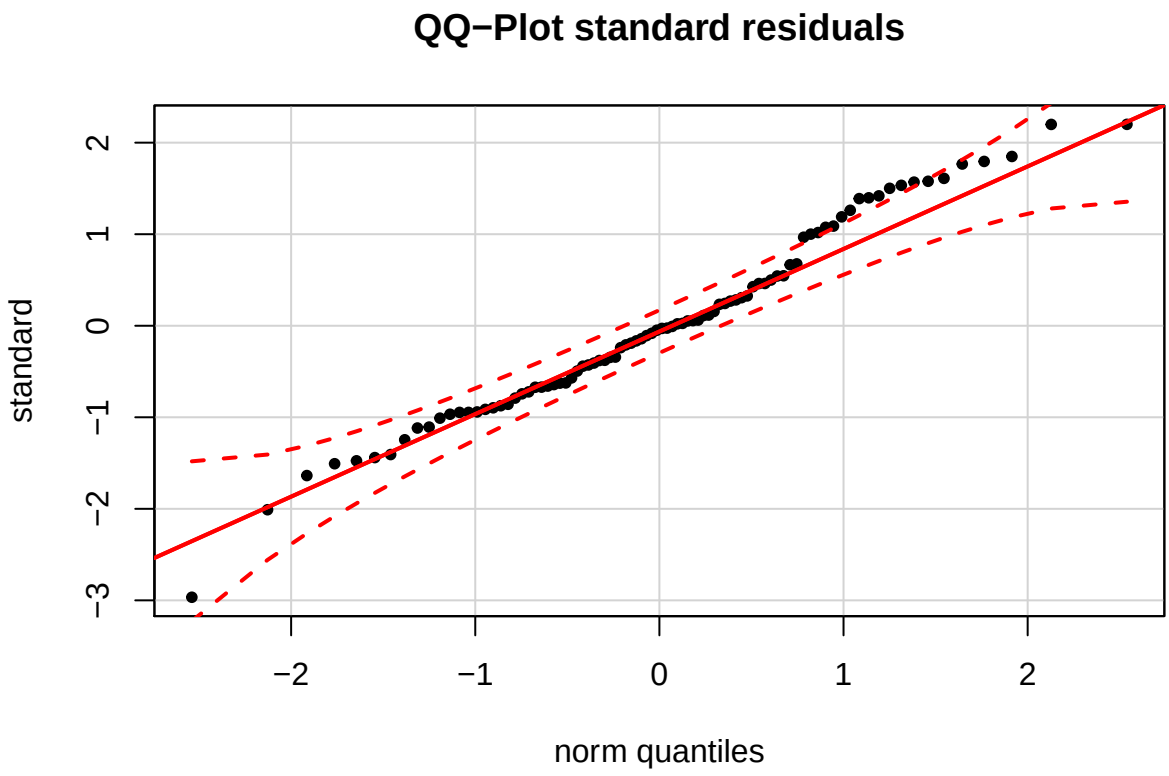
```
# normality of standard residuals
standard <- rstandard(m2)
hist(standard, main="Histogram of standard resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(standard)), col="red", lwd=2, add=TRUE)
```



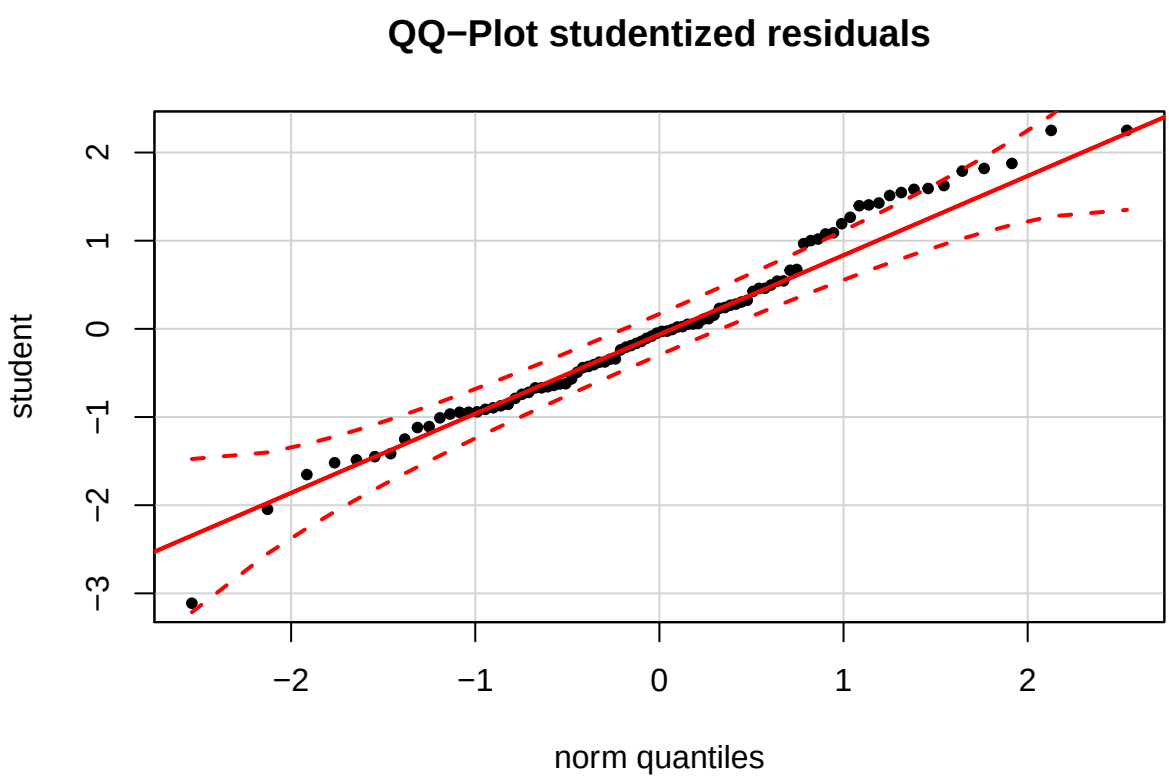

```
# normality of studentized residuals
student <- rstudent(m2)
hist(student, main="Histogram of studentized resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(student)), col="red", lwd=2, add=TRUE)
```




```r
# QQ plot standard residuals
qqPlot(standard, distribution="norm", pch=20, main="QQ-Plot standard residuals")
qqline(standard, col="red", lwd=2)
```




```r
# QQ plot studentized residuals
qqPlot(student, distribution="norm", pch=20, main="QQ-Plot studentized residuals")
qqline(student, col="red", lwd=2)
```



The histograms in particular appear to be fairly normally distributed, while the Q-Q plot doesn't deviate significantly from normality either, so overall the residuals appear to be fairly normal. Notably the log transformation of views has helped to produce normal errors.

Is the assumption valid? *Yes*

Response: *No response required.*

TODO: * One model that includes the previous covariates, and most, if not all, other covariates. A key purpose of this model is to demonstrate the robustness of your results to model specification.

```
m3 <- lm(log(crmrte) ~ log(density) + taxpc + urban + central + west, data=data)
```

CLM 1 - A linear model

The model is specified such that the dependent variable is a linear function of the explanatory variables. Is the assumption valid? *Yes*

Response: No response required.

CLM 2 - Random Sampling

TODO

CLM 3 - Multicollinearity

```
# show correlation
data$log.density <- log(data$density)
cor(data.matrix(subset(data, select=c("density", "log.density", "taxpc", "urban"))))
```

```
##                density log.density     taxpc     urban
## density     1.0000000   0.8896747 0.3204737 0.8206825
## log.density 0.8896747   1.0000000 0.1841222 0.6490078
## taxpc       0.3204737   0.1841222 1.0000000 0.3457462
## urban       0.8206825   0.6490078 0.3457462 1.0000000
```

```
# show vif
vif(m2)
```

```
## log(density)        taxpc        urban
##     1.733261     1.139396     1.901850
```

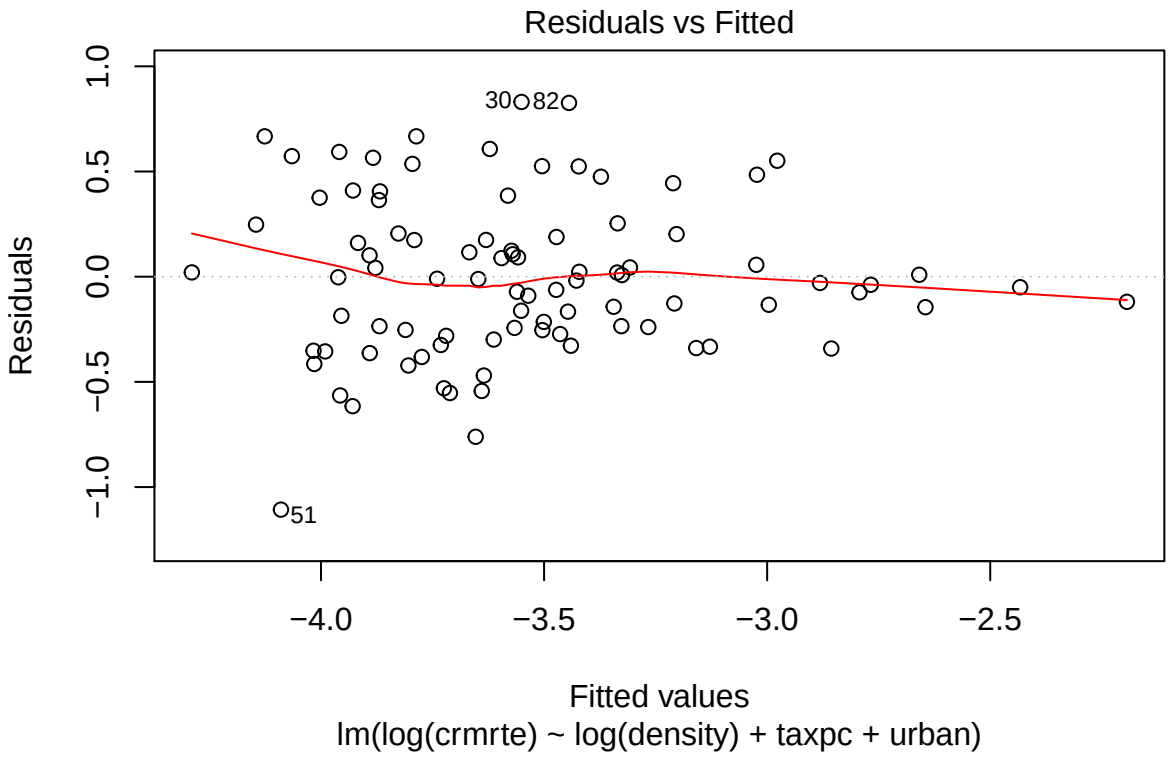
The two explanatory variables (log.density and taxpc) are not perfectly correlated and the VIFs are low (less than 4), so there is no perfect multicollinearity of the independent variables.

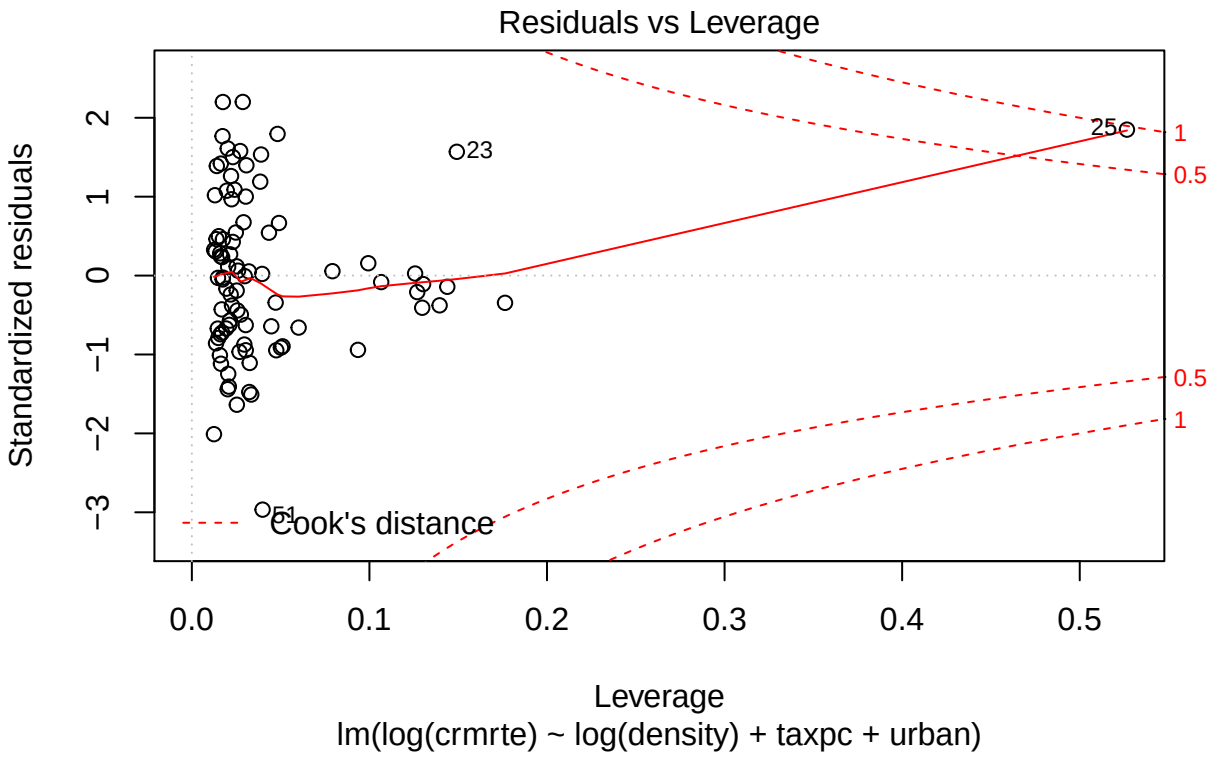
Is the assumption valid? *Yes*

Response: No response required.

CLM 4 - Zero-Conditional Mean

```
plot(m2, which=c(1, 5))
```


Residuals vs Fitted
Residuals
1.0
0.5
0.0
−0.5
−1.0
30
82
51
−4.0
−3.5
−3.0
−2.5
Fitted values
lm(log(crmrte) ~ log(density) + taxpc + urban)




```
# exogenous check
cov(log(data$density), m2$residuals)
```

```
## [1] -8.492333e-18
```

```
cov(data$taxpc, m2$residuals)
```

```
## [1] -3.523097e-16
```

```
# TODO: figure out what to do with covariate
cov(data$urban, m2$residuals)
```

```
## [1] 9.501997e-19
```

The covariances of the two independent variables with the residuals are very close to zero indicating they are likely exogenous.

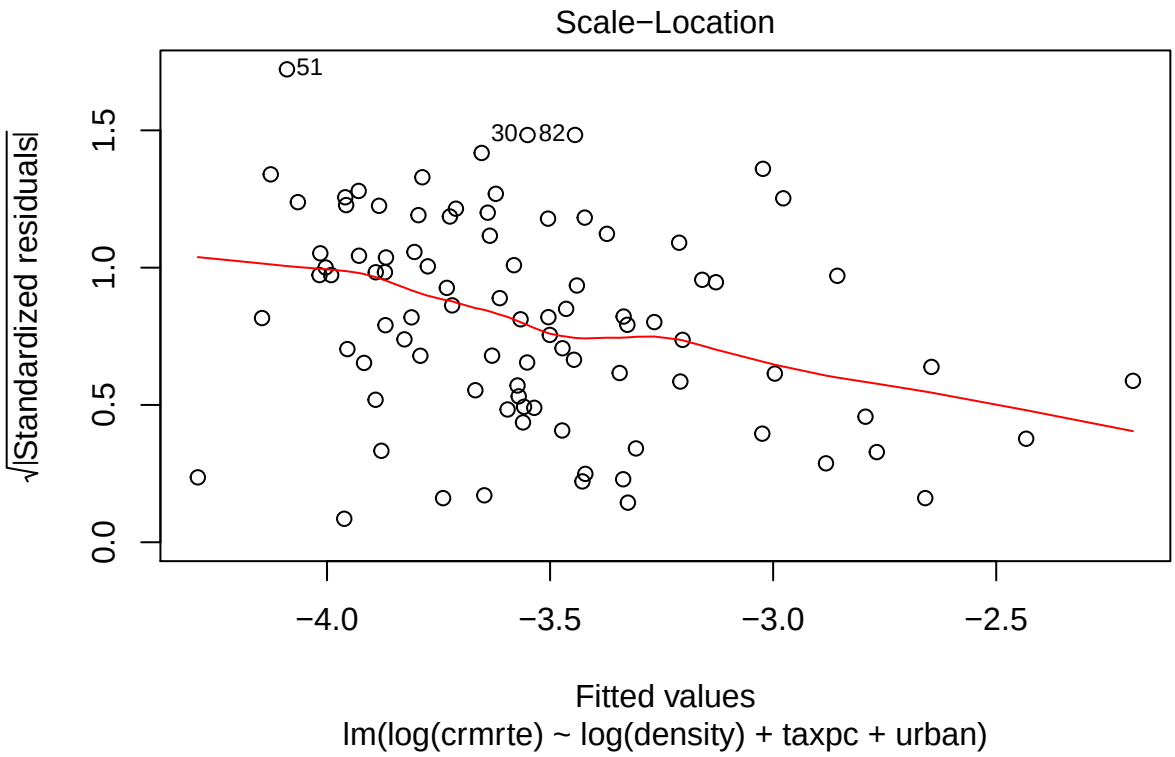
There is a data point with a large Cook's distance.

Is the assumption valid?

Response:

CLM 5 - Homoscedasticity

```
# spreadLevelPlot(m1)
plot(m2, which=3)
```




```
bptest(m2)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  m2
## BP = 7.708, df = 3, p-value = 0.05245
```

not significant p-value for Breusch-Pagan test -> assumption of homoscedasticity met

```
ncvTest(m2)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 7.064728    Df = 1     p = 0.007861626
```

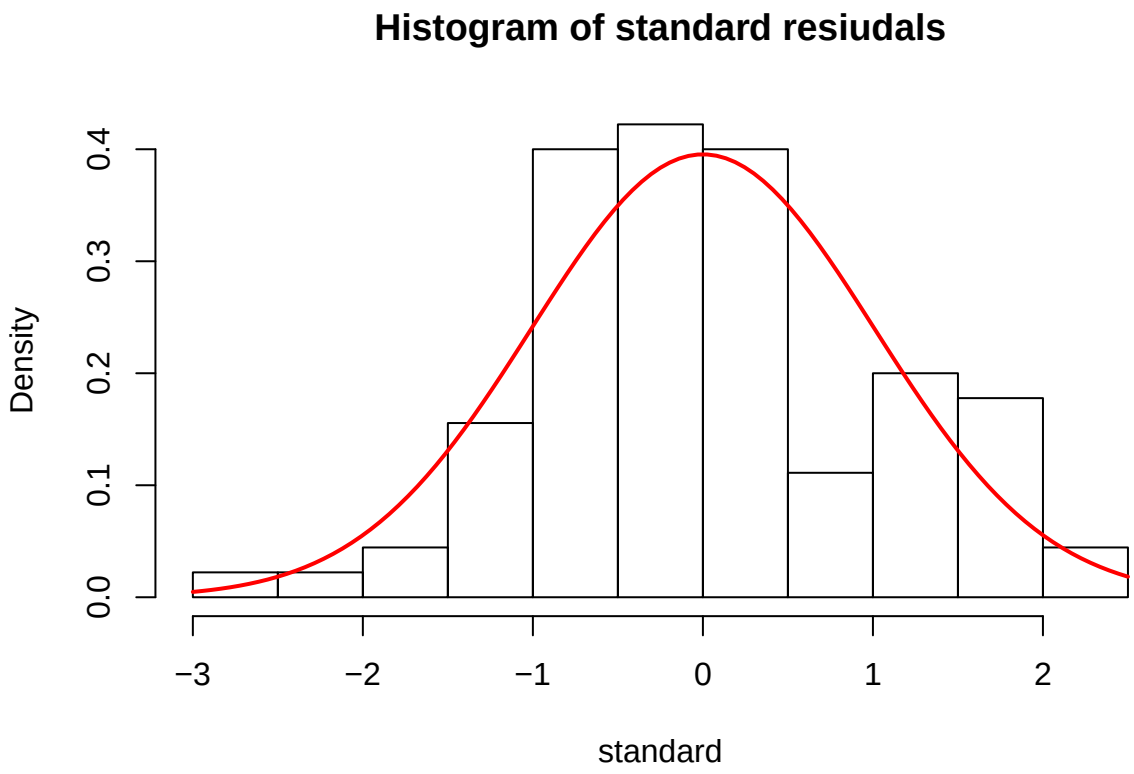
significant p-value for Score Test -> assumption of homoscedasticity met

Is the assumption valid? *Yes*

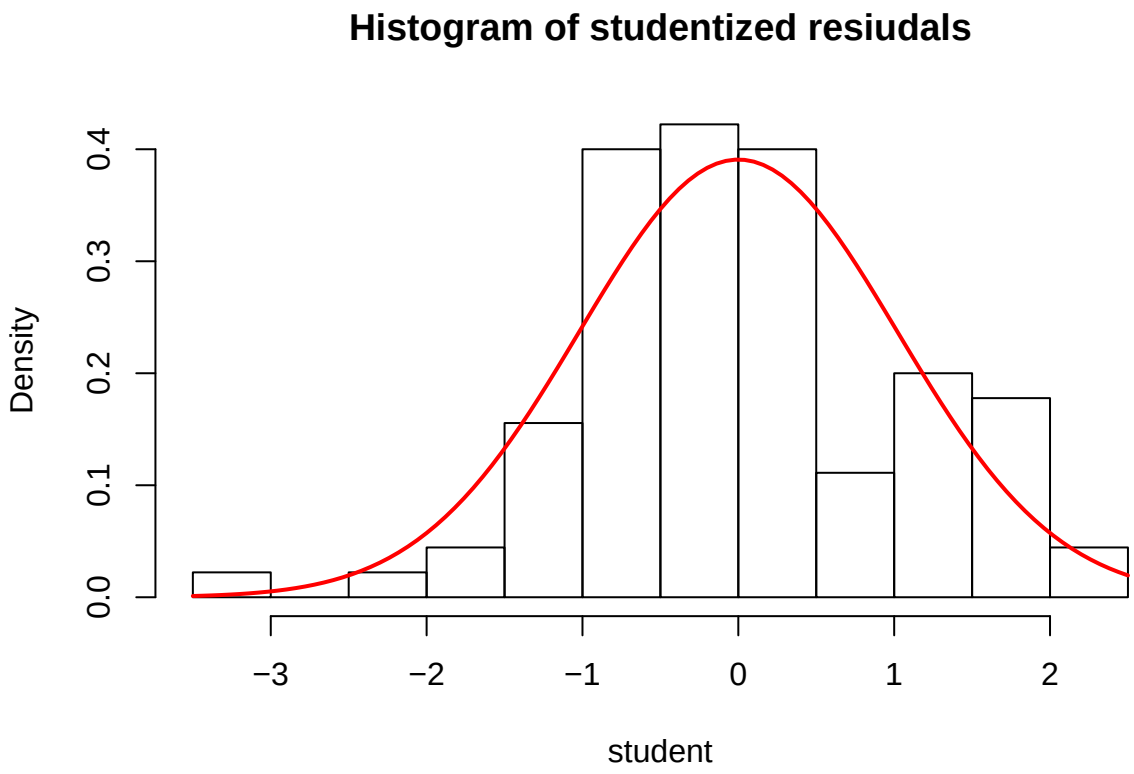
Response:

CLM 6 - Normality of residuals

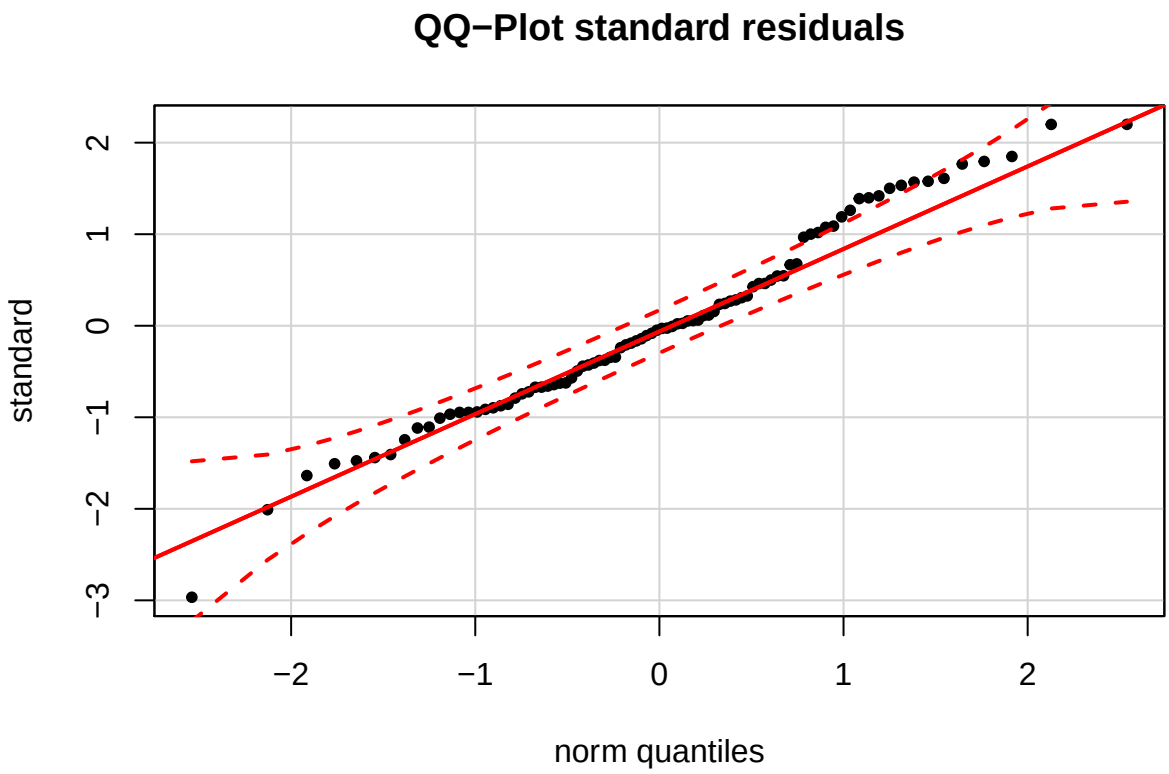
```
# normality of standard residuals
standard <- rstandard(m2)
hist(standard, main="Histogram of standard resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(standard)), col="red", lwd=2, add=TRUE)
```



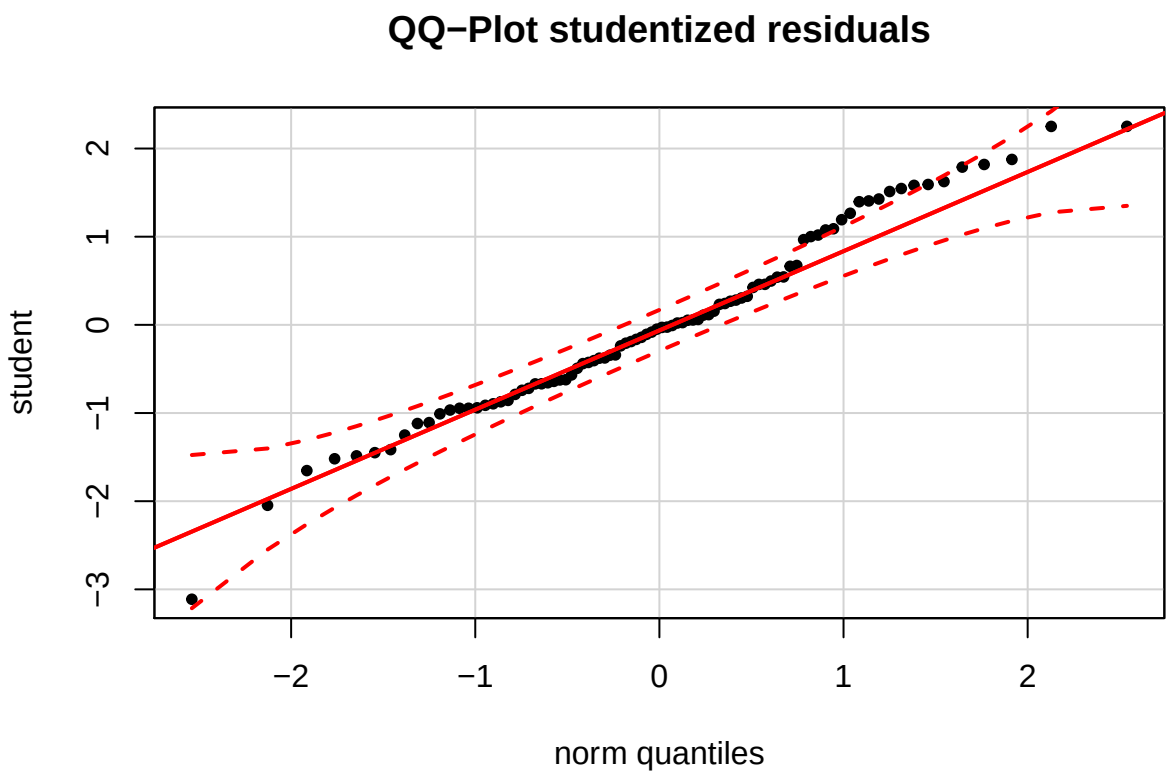

```
# normality of studentized residuals
student <- rstudent(m2)
hist(student, main="Histogram of studentized resiudals", freq=FALSE)
curve(dnorm(x, mean=0, sd=sd(student)), col="red", lwd=2, add=TRUE)
```




```r
# QQ plot standard residuals
qqPlot(standard, distribution="norm", pch=20, main="QQ-Plot standard residuals")
qqline(standard, col="red", lwd=2)
```




```r
# QQ plot studentized residuals
qqPlot(student, distribution="norm", pch=20, main="QQ-Plot studentized residuals")
qqline(student, col="red", lwd=2)
```



The histograms in particular appear to be fairly normally distributed, while the Q-Q plot doesn't deviate significantly from normality either, so overall the residuals appear to be fairly normal. Notably the log transformation of views has helped to produce normal errors.

Is the assumption valid? *Yes*

Response: *No response required.*

Model Results

TODO: A well-formatted regression table summarizing your model results. Make sure that standard errors presented in this table are valid. Also, be sure to comment on both statistical and practical significance.

```
se.m1 <- coef(summary(m1))[, "Std. Error"]
se.m2 <- coef(summary(m2))[, "Std. Error"]
se.m3 <- coef(summary(m3))[, "Std. Error"]
stargazer(m1, m2, m3, se=list(se.m1, se.m2, se.m3), omit.stat=c("f", "ser"),
          star.cutoffs=c(0.05, 0.01, 0.001),
          type="latex", title="Linear Models Predicting Crime Rates")
```

```
##
## % Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvar
## % Date and time: Wed, Dec 06, 2017 - 03:07:54
## \begin{table}[!htbp] \centering
##   \caption{Linear Models Predicting Crime Rates}
##   \label{}
```

```
## \begin{tabular}{@{\extracolsep{5pt}}lccc}
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{3}{c}{\textit{Dependent variable:}} \\
## \cline{2-4}
## \\[-1.8ex] & \multicolumn{3}{c}{log(crmrte)} \\
## \\[-1.8ex] & (1) & (2) & (3)\\
## \hline \\[-1.8ex]
##  log(density) & 0.455$^{***}$ & 0.464$^{***}$ & 0.488$^{***}$ \\
##   & (0.052) & (0.068) & (0.063) \\
##   & & & \\
##  taxpc & 0.010$^{**}$ & 0.010$^{**}$ & 0.007$^{*}$ \\
##   & (0.003) & (0.003) & (0.003) \\
##   & & & \\
##  urban &  & $-$0.043 & $-$0.015 \\
##   &  & (0.195) & (0.168) \\
##   & & & \\
##  central &  &  & $-$0.306$^{***}$ \\
##   &  &  & (0.085) \\
##   & & & \\
##  west &  &  & $-$0.515$^{***}$ \\
##   &  &  & (0.091) \\
##   & & & \\
##  Constant & $-$3.931$^{***}$ & $-$3.936$^{***}$ & $-$3.589$^{***}$ \\
##   & (0.125) & (0.128) & (0.125) \\
##   & & & \\
## \hline \\[-1.8ex]
## Observations & 90 & 90 & 90 \\
## R$^{2}$ & 0.534 & 0.534 & 0.669 \\
## Adjusted R$^{2}$ & 0.523 & 0.518 & 0.649 \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{3}{r}{$^{*}$p$<$0.05; $^{**}$p$<$0.01; $^{***}$p$<$0.001} \\
## \end{tabular}
## \end{table}
```

Causality

TODO: A detailed discussion of causality. In particular, include a discussion of what variables are not included in your analysis and the likely direction of omitted variable bias. Highlight any coefficients you find that appear to have the wrong sign from a causal perspective, and explain why this is the case.

Conclusion

TODO: A brief conclusion with a few high-level takeaways.