Lab3 YZ Draft

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```r
#setwd("/home/yulia/Documents/MIDS/W203/Lab_3/")
crime <- read.csv("crime_v2.csv", stringsAsFactors = FALSE)
crime <- na.omit(crime)
#str(crime)
```

```r
crime$prbconv <- as.numeric(crime$prbconv)
crime$county <- NULL
crime$year <- NULL
```

```r
crime_summary <- data.frame(t(mapply(summary, crime)))
#str(crime_summary)
crime_summary <- crime_summary[,c("Min.","Mean","Max.")]
crime_summary$Min. <- round(crime_summary$Min.,5)
crime_summary$Mean <- round(crime_summary$Mean,4)
crime_summary$Max. <- round(crime_summary$Max.,4)
```


```r
crime_summary <- data.frame(t(mapply(summary, crime)))
#str(crime_summary)
crime_summary <- crime_summary[,c("Min.","Mean","Max.")]
crime_summary$Min. <- round(crime_summary$Min.,5)
crime_summary$Mean <- round(crime_summary$Mean,4)
crime_summary$Max. <- round(crime_summary$Max.,4)
```


```r
kable(crime_summary, booktabs = TRUE) %>%
  kable_styling(font_size = 7)
```

	Min.	Mean	Max.
crmrte	0.00553	0.0334	0.0990
prbarr	0.09277	0.2949	1.0909
prbconv	0.06838	0.5513	2.1212
prbpris	0.15000	0.4108	0.6000
avgsen	5.38000	9.6468	20.7000
polpc	0.00075	0.0017	0.0091
density	0.00002	1.4288	8.8277
taxpc	25.69287	38.0551	119.7615
west	0.00000	0.2527	1.0000
central	0.00000	0.3736	1.0000
urban	0.00000	0.0879	1.0000
pctmin80	1.28365	25.4955	64.3482
wcon	193.64316	285.3585	436.7666
wtuc	187.61726	411.6680	613.2261
wtrd	154.20900	211.5529	354.6761
wfir	170.94017	322.0982	509.4655
wser	133.04306	275.5642	2177.0681
wmfg	157.41000	335.5887	646.8500
wfed	326.10001	442.9007	597.9500
wsta	258.32999	357.5220	499.5900
wloc	239.17000	312.6808	388.0900
mix	0.01961	0.1288	0.4651
pctymle	0.06216	0.0840	0.2487

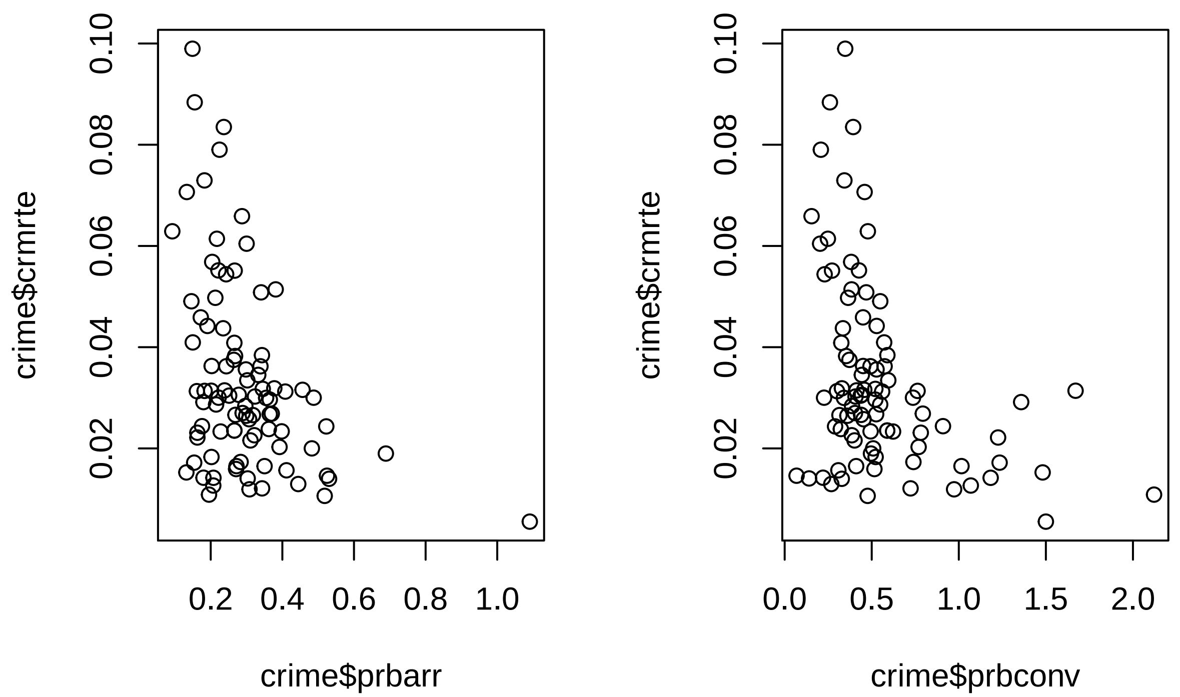
```r
nrow(crime[crime$prbarr >= 1,])
```

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

```r
nrow(crime[crime$prbconv >= 1,])
```

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

```r
par(mfrow=c(1,2))
plot(crime$prbarr, crime$crmrte)
plot(crime$prbconv, crime$crmrte)
```




```r
crime$prbarr_imp <- ifelse(crime$prbarr > 1, mean(crime$prbarr), crime$prbarr)
summary(crime$prbarr)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.09277 0.20568 0.27095 0.29492 0.34438 1.09091
```

```r
summary(crime$prbarr_imp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.09277 0.20568 0.27095 0.28617 0.34323 0.68902
```

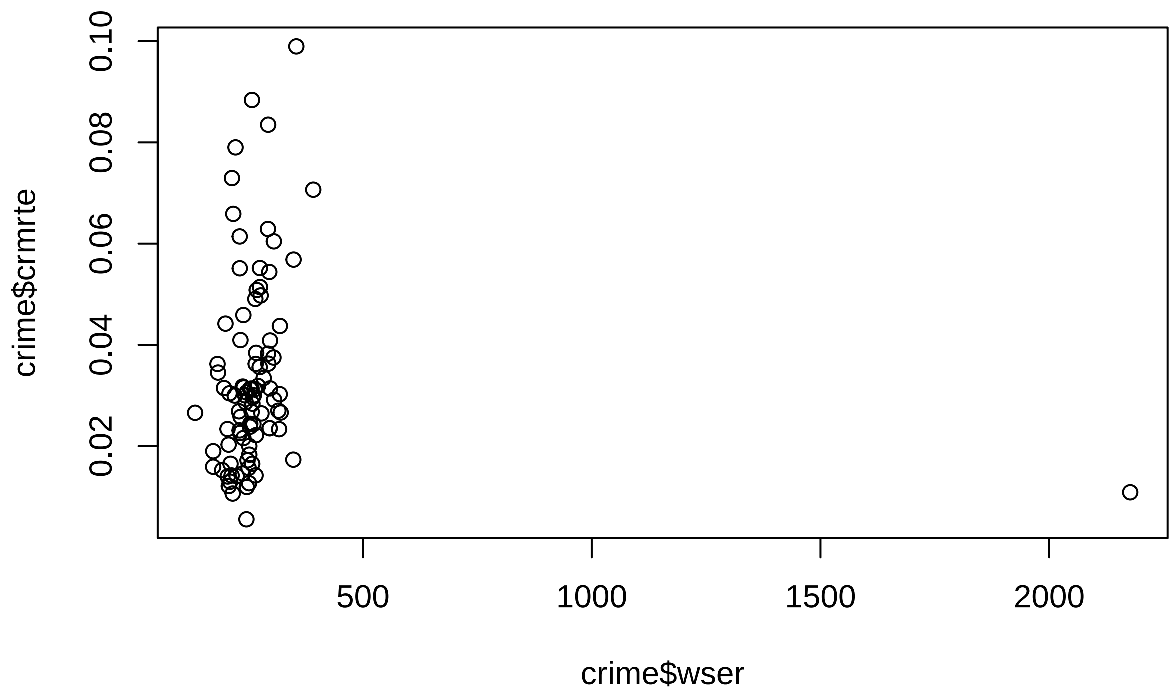
```r
crime$prbconv_imp <- ifelse(crime$prbconv > 1, 1, crime$prbconv)
summary(crime$prbconv)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.06838 0.34541 0.45283 0.55128 0.58886 2.12121
```

```r
summary(crime$prbconv_imp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.06838 0.34541 0.45283 0.50888 0.58886 1.00000
```

```r
plot(crime$wser, crime$crmrte)
```



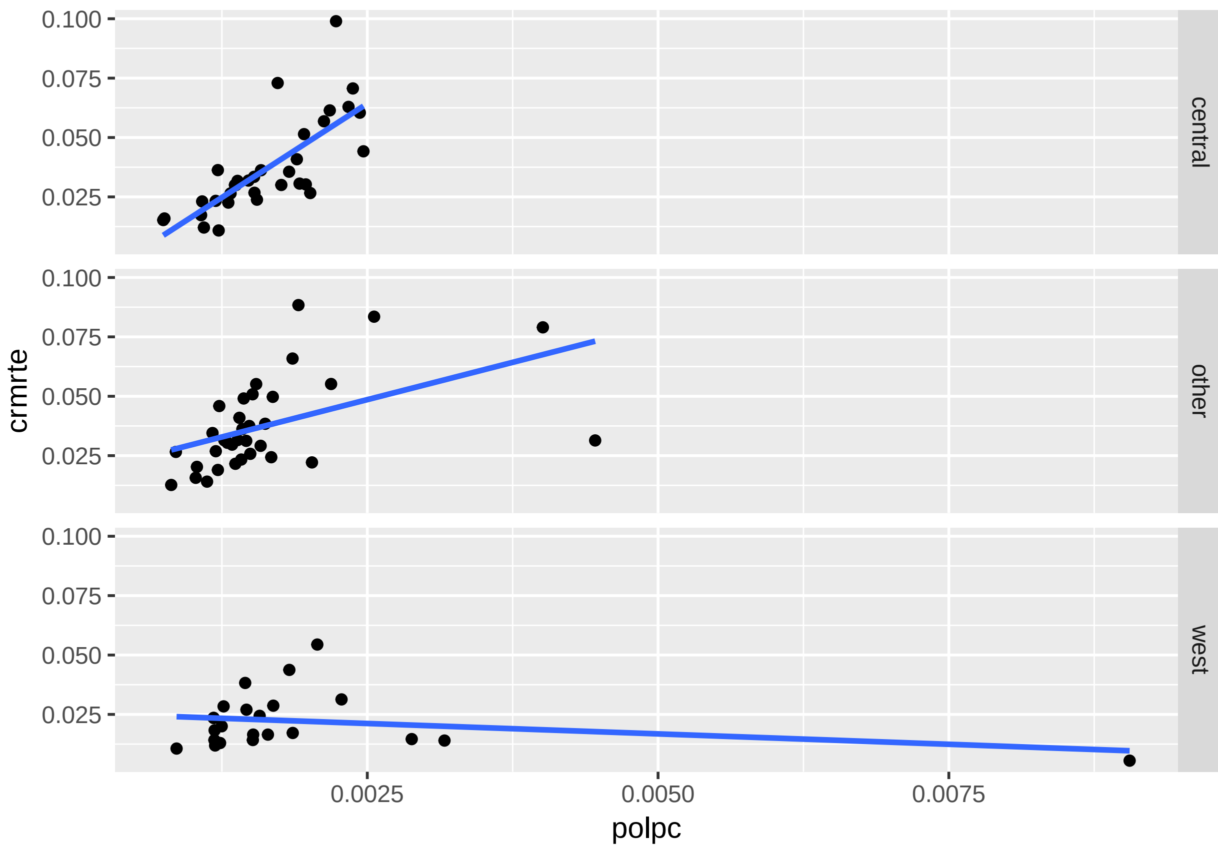

```r
crime$wser_imp <- ifelse(crime$wser > 2000, mean(crime[crime$wser < 2000,]$wser), crime$wser)
summary(crime$wser)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   133.0   229.7   253.2   275.6   280.5  2177.1
```

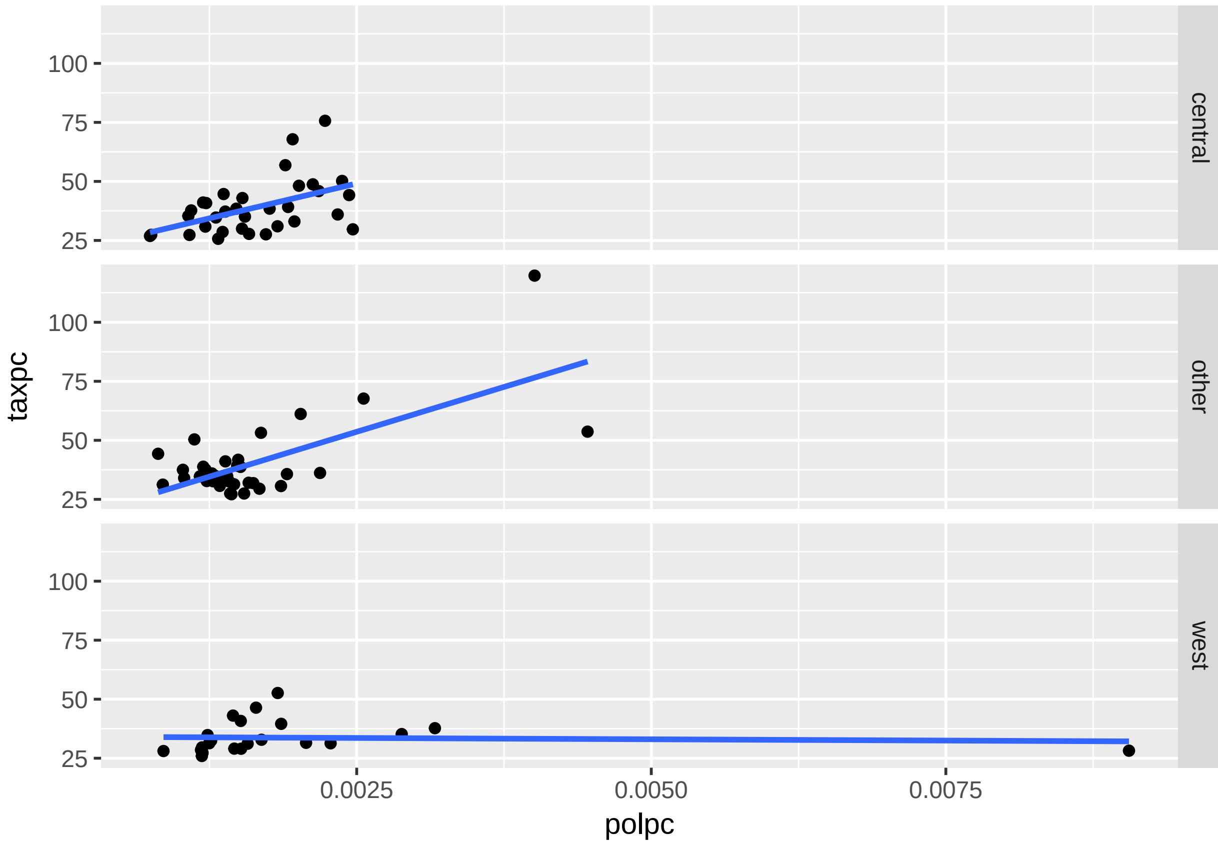
```r
summary(crime$wser_imp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   133.0   229.7   253.2   254.4   277.2   391.3
```

```r
crime$region <- ifelse(crime$west == 1, "west",
                            ifelse(crime$central == 1, "central", "other"))
ggplot(crime, aes(polpc, crmrte)) +
  geom_point() +
  facet_grid(region~.) +
  geom_smooth(method = "lm", se = FALSE)
```




```
ggplot(crime, aes(polpc, taxpc)) +
  geom_point() +
  facet_grid(region~.) +
  geom_smooth(method = "lm", se = FALSE)
```




```
crime$polpc_imp <-
  ifelse(crime$polpc == max(crime$polpc), mean(crime[crime$west == 1,]$polpc), crime$polpc)
summary(crime$polpc)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## 0.0007459 0.0012308 0.0014853 0.0017022 0.0018768 0.0090543
```

```
summary(crime$polpc_imp)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## 0.0007459 0.0012308 0.0014853 0.0016239 0.0018768 0.0044592
```

```
# Prepare a .RData for easier sharing and usage.
ind_variables <- c( 'crmrte',
  'prbarr_imp', 'prbconv_imp', 'prbpris', 'avgsen',
  'polpc_imp', 'density', 'taxpc', 'west', 'central', 'urban', 'pctmin80', 'wcon',
  'wtuc', 'wtrd', 'wfir', 'wser_imp', 'wmfg', 'wfed', 'wsta', 'wloc', 'mix',
  'pctymle'
)
var_labels <- c('crimes committed per person',
  'probability of arrest', 'probability of conviction',
  'probability of prison sentence', 'avg. sentence, days',
  'police per capita', 'people per sq. mile', 'tax revenue per capita',
  '=1 if in western N.C.', '=1 if in central N.C.', '=1 if in SMSA',
  'perc. minority, 1980', 'weekly wage, construction',
  'wkly wge, trns, util, commun', 'wkly wge, whlesle, retail trade',
  'wkly wge, fin, ins, real est', 'wkly wge, service industry',
  'wkly wge, manufacturing', 'wkly wge, fed employees',
```

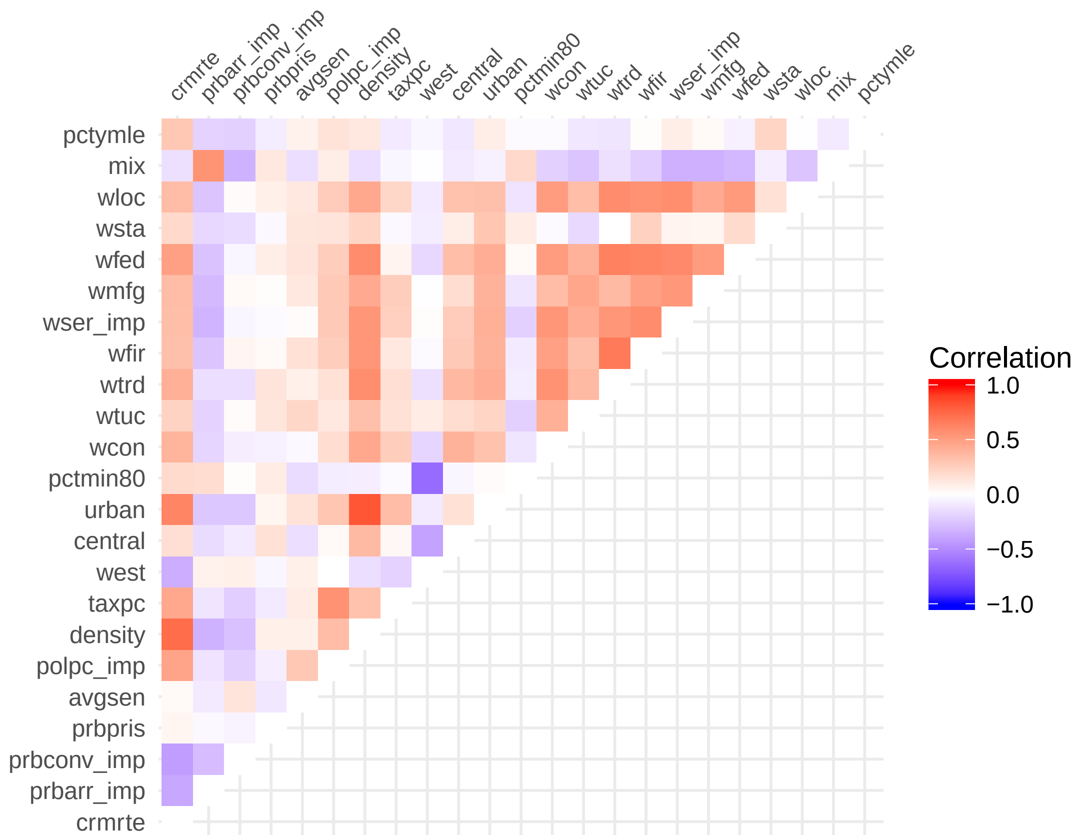
```r
  'wkly wge, state employees', 'wkly wge, local gov emps',
  'offense mix: face-to-face/other', 'percent young male'
)
impact <- c("Dependent",
  "Negative" , "Negative", "Negative", "Negative",
            "Negative", "Positive", "Negative",
            "Unclear", "Unclear", "Unclear", "Unclear",
            "Negative","Negative","Negative",
            "Negative", "Negative", "Negative", "Negative",
            "Negative", "Negative", "Unclear","Positive")
control <- c("NA","Yes", "Yes", "Yes", "Yes",
             "Yes", "No", "Yes",
             "No", "No", "No","No",
             "Yes", "Yes", "Yes",
             "Yes", "Yes", "Yes", "Yes",
             "Yes", "Yes", "No", "No")
cor_w_crimerate <- round(cor(crime[,ind_variables])[1,],2)
desc <- data.frame(ind_variables, var_labels, impact, cor_w_crimerate, control,
                   row.names = NULL)
colnames(desc) <- c("Explanatory Variables",
                    "Explanation",
                    "Expected Impact on Crime Rate",
                    "Correlation w/ Crime Rate",
                    "Can Gov Impact This?")
```

```r
kable(desc, booktabs = TRUE, align = c("llccc")) %>%
  kable_styling(latex_options = c("scale_down"),
               full_width = FALSE) %>%
  row_spec(0, bold = TRUE) %>%
  column_spec(1, width = "8em") %>%
  column_spec(3, width = "10em") %>%
  column_spec(4, width = "8em") %>%
  column_spec(5, width = "9em")
```

Explanatory Variables	Explanation	Expected Impact on Crime Rate	Correlation w/ Crime Rate	Can Gov Impact This?
crmrte	crimes committed per person	Dependent	1.00	NA
prbarr_imp	probability of arrest	Negative	-0.38	Yes
prbconv_imp	probability of conviction	Negative	-0.42	Yes
prbpris	probability of prison sentence	Negative	0.05	Yes
avgsen	avg. sentence, days	Negative	0.03	Yes
polpc_imp	police per capita	Negative	0.47	Yes
density	people per sq. mile	Positive	0.73	No
taxpc	tax revenue per capita	Negative	0.45	Yes
west	=1 if in western N.C.	Unclear	-0.35	No
central	=1 if in central N.C.	Unclear	0.17	No
urban	=1 if in SMSA	Unclear	0.62	No
pctmin80	perc. minority, 1980	Unclear	0.19	No
wcon	weekly wage, construction	Negative	0.39	Yes
wtuc	wkly wge, trns, util, commun	Negative	0.23	Yes
wtrd	wkly wge, whlesle, retail trade	Negative	0.41	Yes
wfir	wkly wge, fin, ins, real est	Negative	0.33	Yes
wser_imp	wkly wge, service industry	Negative	0.34	Yes
wmfg	wkly wge, manufacturing	Negative	0.35	Yes
wfed	wkly wge, fed employees	Negative	0.49	Yes
wsta	wkly wge, state employees	Negative	0.20	Yes
wloc	wkly wge, local gov emps	Negative	0.35	Yes
mix	offense mix: face-to-face/other	Unclear	-0.13	No
pctymle	percent young male	Positive	0.29	No

```
cor_mat <- round(cor(crime[,ind_variables]),2)
get_upper_tri <- function(cor_mat){
    cor_mat[lower.tri(cor_mat)]<- NA
    return(cor_mat)
}
cor_mat_upper <- get_upper_tri(cor_mat)
cor_mat_upper2 <- melt(cor_mat_upper, na.rm = TRUE)
cor_mat_upper2[cor_mat_upper2$value == 1,]$value <- 0
```

```
ggplot(data = cor_mat_upper2, aes(Var1, Var2, fill = value)) +
  geom_tile() +
  scale_fill_gradient2(low = "blue", high = "red", mid = "white",
                       midpoint = 0, limit = c(-1,1), space = "Lab",
                       name = "Correlation") +
  theme_minimal() +
  scale_x_discrete(position = "top") +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, size = 8, hjust = 0),
        axis.title.x=element_blank(),
        axis.title.y=element_blank()) +
  coord_fixed()
```




```
ind_vars_transf <- c("wcon", "wtuc", "wtrd", "wfir",
                     "wser", "wser_imp", "wmfg", "wfed", "wsta", "wloc",
                     "prbarr", "prbarr_imp", "prbconv", "prbconv_imp", "prbpris", "avgsen",
                       "polpc_imp", "density", "taxpc", "pctmin80", "mix", "pctymle")
crime[paste(ind_vars_transf,"ln",sep = ".")] <- log(crime[ind_vars_transf])
crime[paste(ind_vars_transf,"sq",sep = ".")] <- (crime[ind_vars_transf])**2
```

The Model Building Process

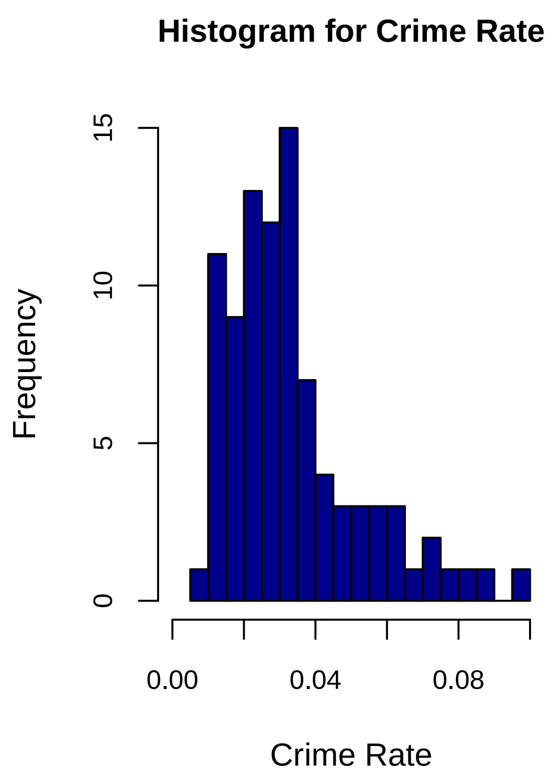
Dependent variable

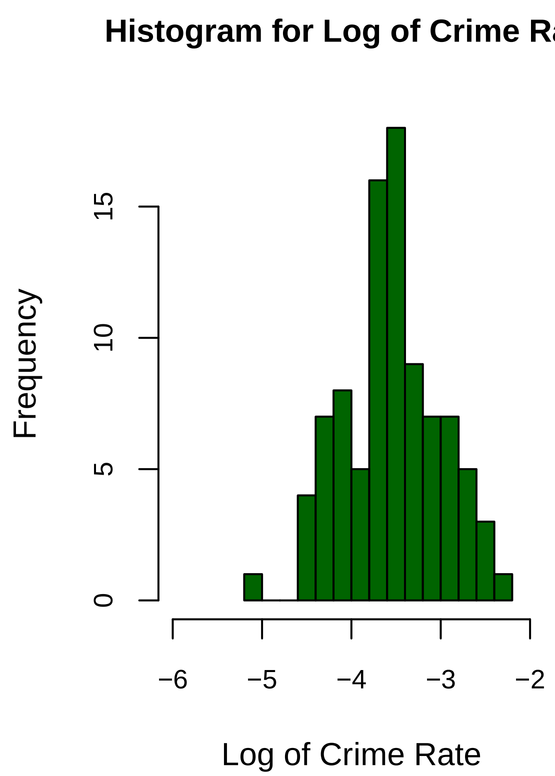
Our main dependent variable is crime rate *crmrte*. It is defined as "Crimes committed per person". After careful consideration, in order for us to understand the impact of our main causal effects (probability of arrest and probability of conviction) onto crime rate, we decided to transform our dependent variable by taking a natural log. This would allow us to interprete the coefficients of our predictive factors as elasticities: if probability of arrest goes up by x points, then the crimte rate decreases by y% (assuming our initial hypothesis is tru and *prbarr* has a negative effect). If we were to keep the variable as it is, we would interpret the coefficient for *prbarr* as: f probability of arrest goes up by x points, then the crimte rate decreases by y crimes per person. However, this interpretation does not allow us to judge the practical significance of the effect (is that y big of small?).

Let's take a look at histograms for *crmrte* (as it is and transformed):

```
par(mfrow=c(1,2))
hist(crime$crmrte,
     breaks = 15,
     xlim = c(0,0.1),
```

```
     col = "darkblue",
     cex.main = 1,
     cex.axis = 0.8,
     xlab = "Crime Rate",
     main = "Histogram for Crime Rate")
hist(log(crime$crmrte),
     breaks = 15,
     xlim = c(-6,-2),
     cex.main = 1,
     cex.axis = 0.8,
     xlab = "Log of Crime Rate",
     col = "darkgreen",
     main = "Histogram for Log of Crime Rate")
```





Based on the above charts, *crmrte* is skewed towards the right tale (there is a number of counties with large crime rates). The log of *crmrte*, on the other hand, looks normally distributed. This definition of the dependent variables might help us build a model with a better fit.

Main control variables

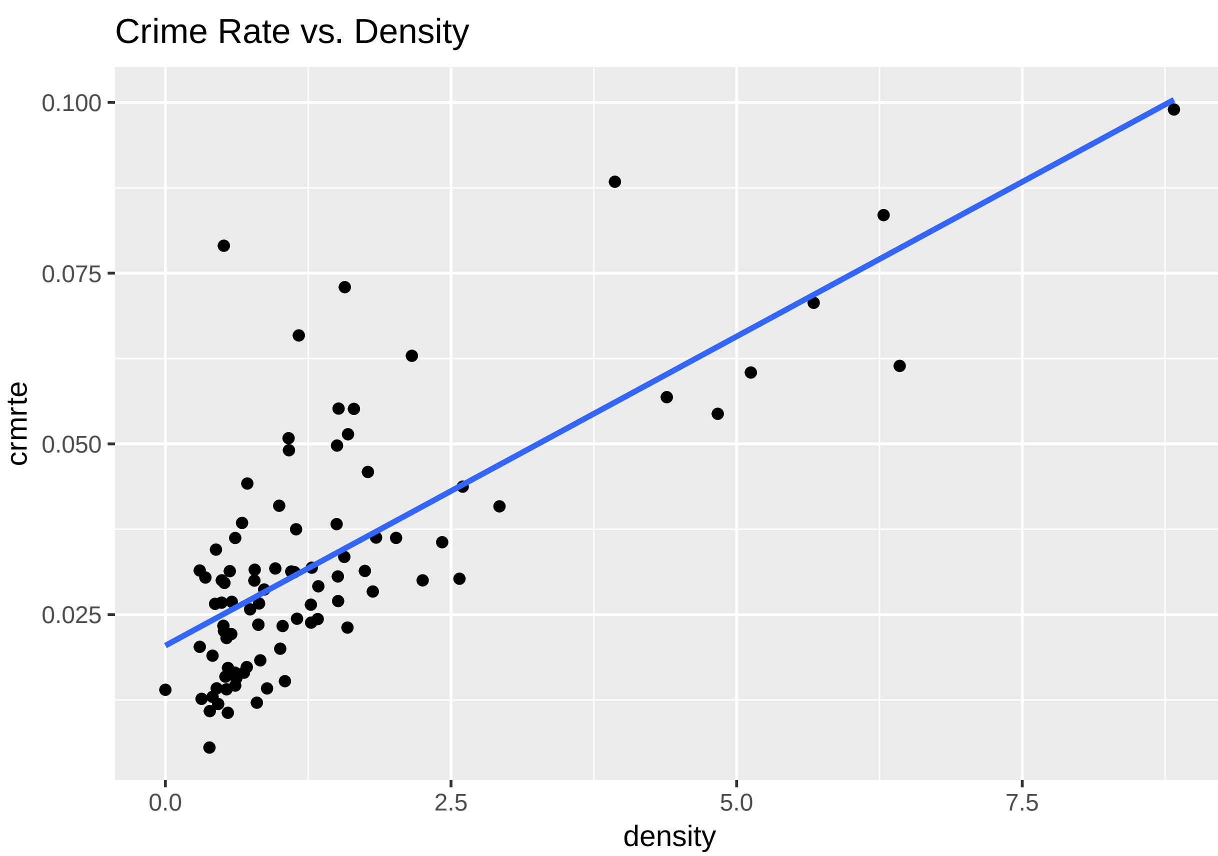
Our primary focus in this analysis is two variables *prbarr* and *prbconv* (the third probability variable *prbpris* has weak correlation with crime rate and didn't show up in any of our models as statistically significant. Most likely it's because the idea of prison sentence is too far from the act of crime and doesn't affect the behavior). We will try to understand how probability of arrest *prbarr* and probability of conviction *prbconv* impact crime rate. If they are strong causal factors, we can define policies that influence these two factors and, hence, help us lower crime rates across counties. Earlier in this report, we hypothesised that these two variables will have negative impact on our dependent variable: the higher the probabilities of arrest and conviction, the lower the crime rate. However, before building a model with these two variables, we want to make a case of including two more variables in our first model: *density* and *west*. First, consider the crime rate by region (we recoded the third region as "other" for analysis purposes):

```
crime$region <- ifelse(crime$west == 1, "west",
                       ifelse(crime$central == 1, "central", "other"))
aggregate(crmrte ~ region, data = crime, mean)
```

```
##    region     crmrte
## 1 central 0.03699627
## 2   other 0.03739491
## 3    west 0.02216183
```

Based on the table above, crime rate in West region is lower than in Central and Other. Hence, we need to control for regionality in order to get an unbiased read on two selected probability variables. On the other hand, density has the hieghest correlation with crime rate (0.73). And the chart below clearly support strong linear relationship between two variables:

```
ggplot(crime, aes(density, crmrte)) +
  geom_point() +
  #facet_grid(region~.) +
  geom_smooth(method = "lm", se = FALSE) +
  ggtitle("Crime Rate vs. Density")
```



We also know that *west* and *density* have different relationship with *crmrte* because even though crime rate is the lowest in the West, density is the highest in Central region. Hence, we need both *west* and *density* in our initial model to get unbiased estimates of *prbarr* and *prbconv*.

```r
aggregate(density ~ region, data = crime, mean)
```

```
##    region  density
## 1 central 2.047960
## 2   other 1.085503
## 3    west 1.062994
```

Note: we tested *central* and *urban* in our models and they were not signicant predictors for crime rate.

Model #1

Our first model contains four variables: *density*, *west*, *prbarr*, *prbconv*. The coefficients for these variables are:

```r
ind_vars1 <- c("density", "west", "prbarr", "prbconv")
crmrte_formula1 <- as.formula(paste("log(crmrte) ~", paste(ind_vars1, collapse = "+"), sep = ""))
crmrte_lm1 <- lm(crmrte_formula1, data = crime)
crmrte_lm1$coefficients
```

```
## (Intercept)     density        west      prbarr     prbconv
##  -2.9896995   0.1502191  -0.3564719  -1.2691367  -0.5524672
```

Coefficient interpretation:

- *density* 0.15: for each person per sq.mile increase in density, crime rate increases by 0.15% when everything else stays the same
- *west* -0.36: crime rate in the West is 0.36% lower than in Central and Other regions on average (and controling for all other factors)
- *prbarr* -1.27: for each point increase in probability of arrest crime rate decreases by 1.27%
- *prbconv* -0.55: for each point increase in probability of arrest crime rate decreases by 0.55%

As we can see, our initial hypothesis has been confirmed: both probability variables have negative impact on crime rate. Moreover, one-point change in probability of arrest has larger impact on crime rate than one-point change in probability of conviction. This confirms our hypothesis that probability of arrest has stronger effect on crime rate because it's closer to the act of crime (being arrested is easier to imagine than being convicted).

The adj R^2 for this model is 67.7%:

```r
summary(crmrte_lm1)$adj.r.squared
```

```
## [1] 0.6770812
```

And all of the coefficients are statistically significant when we adjust for heteroscadasticity:

```r
coeftest(crmrte_lm1, vcov = vcovHC)
```

```
##
## t test of coefficients:
##
##              Estimate Std. Error  t value  Pr(>|t|)
## (Intercept) -2.989700   0.197646 -15.1265 < 2.2e-16 ***
## density      0.150219   0.026222   5.7286 1.460e-07 ***
## west        -0.356472   0.071109  -5.0130 2.840e-06 ***
## prbarr      -1.269137   0.393581  -3.2246  0.001784 **
## prbconv     -0.552467   0.131595  -4.1982 6.532e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note: we will analyze the residuals later on, after we develop all three models.

```r
ind_vars2 <- c("density", "west", "prbarr", "prbconv", "polpc_imp.ln", "pctmin80",
               "west*polpc_imp.ln")
crmrte_formula2 <- as.formula(paste("log(crmrte) ~", paste(ind_vars2, collapse = "+"), sep = ""))
crmrte_lm2 <- lm(crmrte_formula2, data = crime)
coeftest(crmrte_lm2, vcov = vcovHC)
```

```
##
## t test of coefficients:
##
##                     Estimate Std. Error t value  Pr(>|t|)
## (Intercept)        1.1292993  0.9061841  1.2462 0.2161919
## density            0.1026480  0.0262243  3.9142 0.0001851 ***
## west              -3.6778777  1.7795707 -2.0667 0.0418773 *
## prbarr            -1.4036147  0.5585036 -2.5132 0.0138991 *
## prbconv           -0.5657364  0.1566226 -3.6121 0.0005190 ***
## polpc_imp.ln       0.6549475  0.1366581  4.7926  7.13e-06 ***
## pctmin80           0.0077037  0.0026484  2.9088 0.0046537 **
## west:polpc_imp.ln -0.5394537  0.2736923 -1.9710 0.0520539 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(crmrte_lm2)$adj.r.squared
```

```
## [1] 0.7954901
```

```r
ind_vars_all <- c("prbarr_imp", "prbconv", "prbpris", "avgsen", "polpc_imp.ln", "density", "taxpc.ln",
               "west", "central", "urban", "pctmin80", "wcon.ln", "wtuc.ln", "wtrd.ln", "wfir.ln",
               "wser_imp.ln", "wmfg.ln", "wfed.ln", "wsta.ln", "wloc.ln", "mix", "pctymle")
crmrte_formula_all <- as.formula(paste("log(crmrte) ~", paste(ind_vars_all, collapse = "+"), sep = ""))
crmrte_lm_all <- lm(crmrte_formula_all, data = crime)
coeftest(crmrte_lm_all, vcov = vcovHC)
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value  Pr(>|t|)
## (Intercept)  -1.7998743  4.1019804 -0.4388  0.662211
## prbarr_imp   -1.7045460  0.3084807 -5.5256 5.613e-07 ***
## prbconv      -0.6657768  0.1237328 -5.3808 9.891e-07 ***
## prbpris      -0.1352744  0.4319559 -0.3132  0.755112
## avgsen       -0.0257841  0.0156975 -1.6426  0.105091
## polpc_imp.ln  0.5566838  0.2076812  2.6805  0.009216 **
## density       0.1091624  0.0523409  2.0856  0.040770 *
## taxpc.ln     -0.0462678  0.2337318 -0.1980  0.843673
## west         -0.2297256  0.1219415 -1.8839  0.063855 .
## central      -0.1739208  0.0782520 -2.2226  0.029573 *
## urban        -0.0943715  0.2202114 -0.4285  0.669605
## pctmin80      0.0077879  0.0027426  2.8397  0.005951 **
## wcon.ln       0.3429113  0.2426046  1.4135  0.162083
## wtuc.ln       0.1633127  0.2852024  0.5726  0.568790
## wtrd.ln       0.2496244  0.3060976  0.8155  0.417630
## wfir.ln      -0.1628161  0.3387942 -0.4806  0.632361
## wser_imp.ln  -0.4981123  0.3068452 -1.6233  0.109145
## wmfg.ln      -0.0390599  0.1639415 -0.2383  0.812400
## wfed.ln       0.6942787  0.4334872  1.6016  0.113877
```

```
## wsta.ln       -0.3323233  0.3263517 -1.0183  0.312146
## wloc.ln        0.0468408  0.6851445  0.0684  0.945695
## mix           -0.6559210  0.5589545 -1.1735  0.244698
## pctymle        2.0885832  1.3069442  1.5981  0.114665
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(crmrte_lm_all)$adj.r.squared
```

```
## [1] 0.8193607
```

```
AIC(crmrte_lm1)
```

```
## [1] 52.14778
```

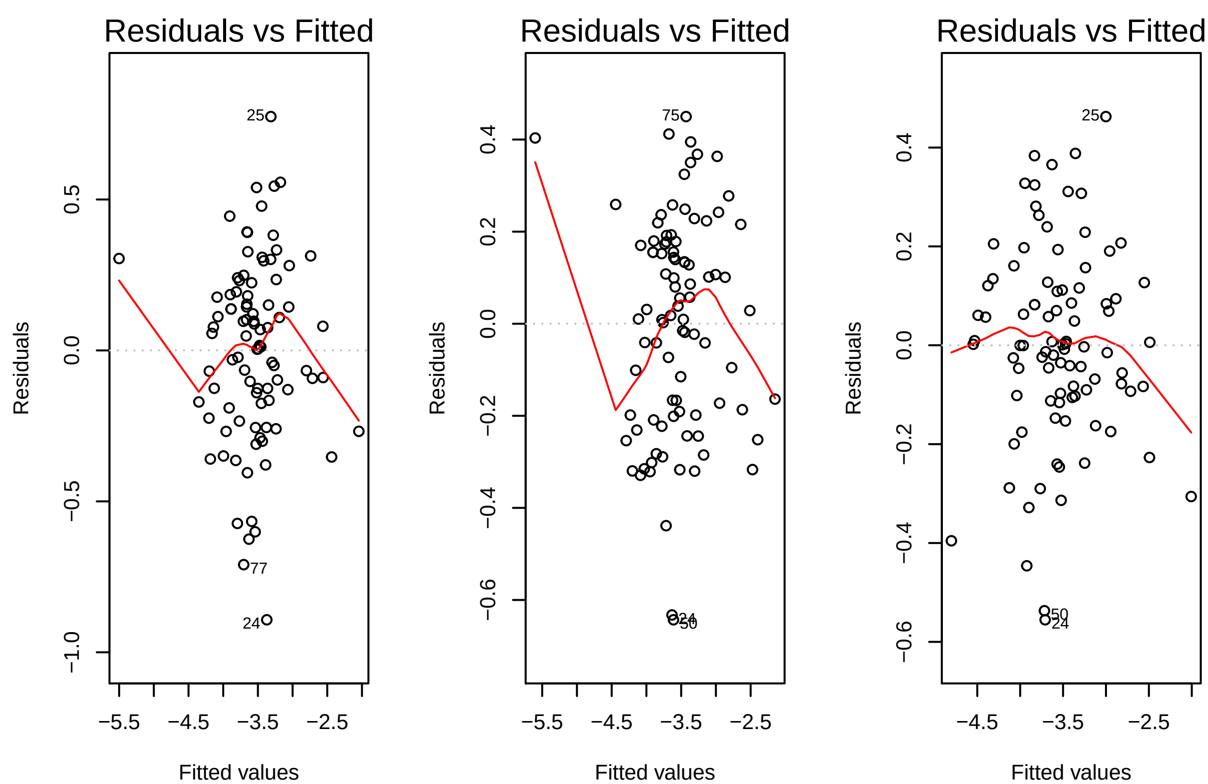
```
AIC(crmrte_lm2)
```

```
## [1] 13.34928
```

```
AIC(crmrte_lm_all)
```

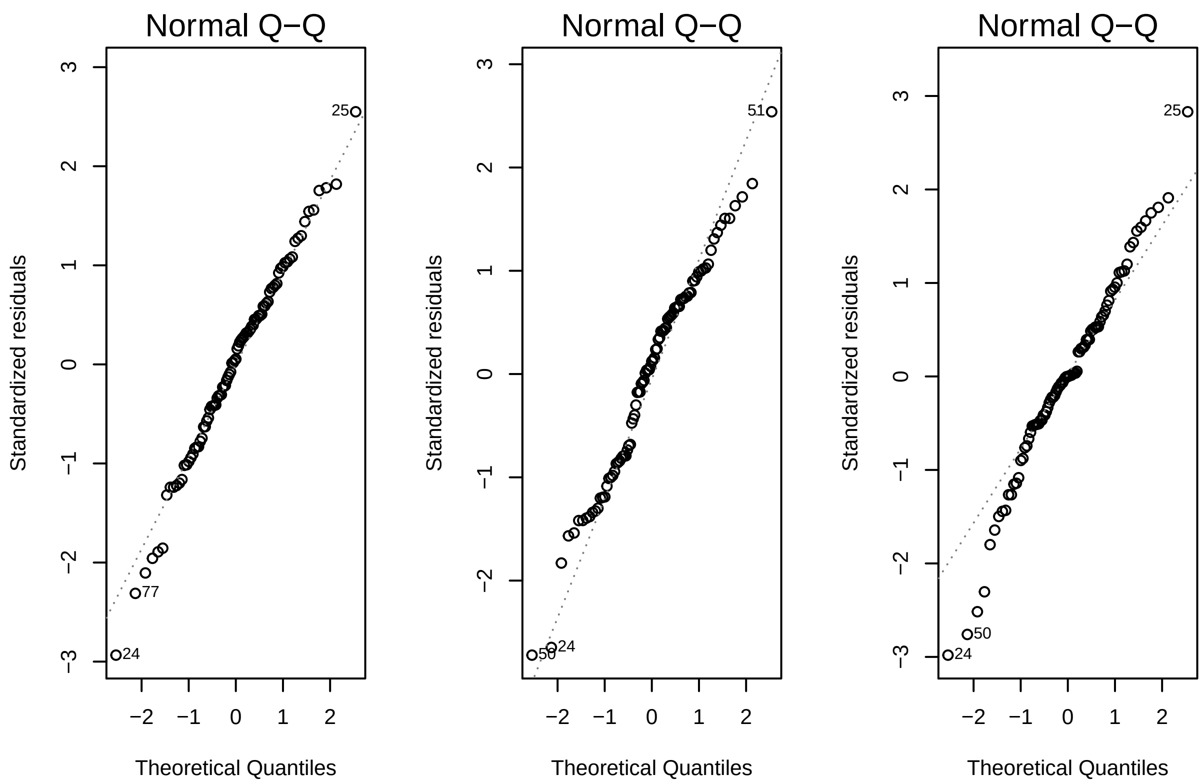
```
## [1] 13.91558
```

```
par(mfrow=c(1,3))
plot(crmrte_lm1, which = 1)
plot(crmrte_lm2, which = 1)
plot(crmrte_lm_all, which = 1)
```

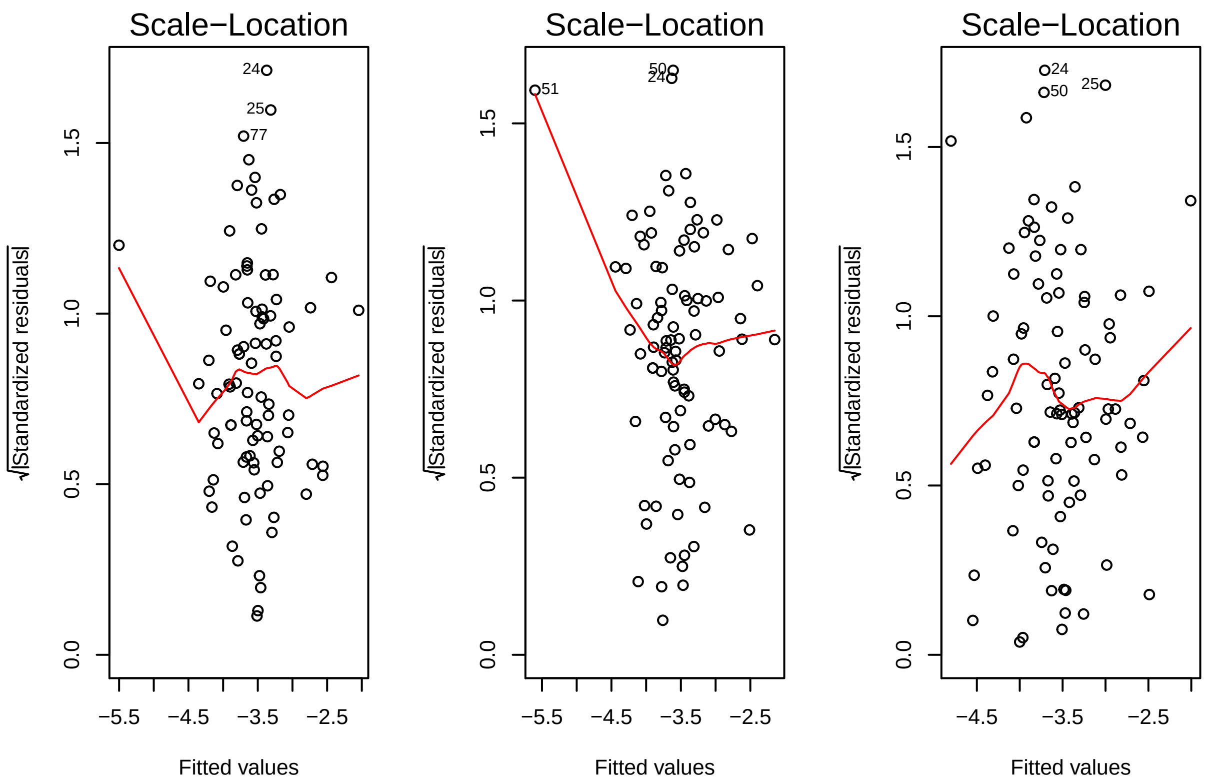



```
par(mfrow=c(1,3))
plot(crmrte_lm1, which = 2)
```

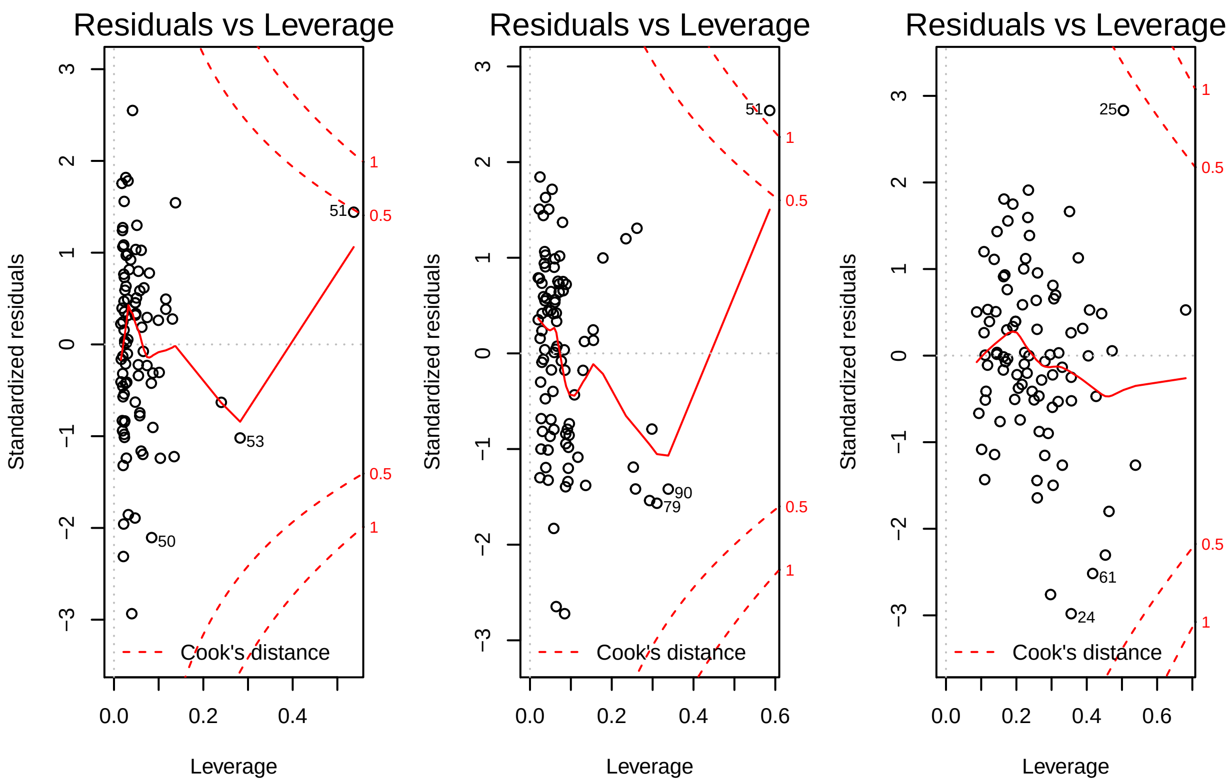
```r
plot(crmrte_lm2, which = 2)
plot(crmrte_lm_all, which = 2)
```



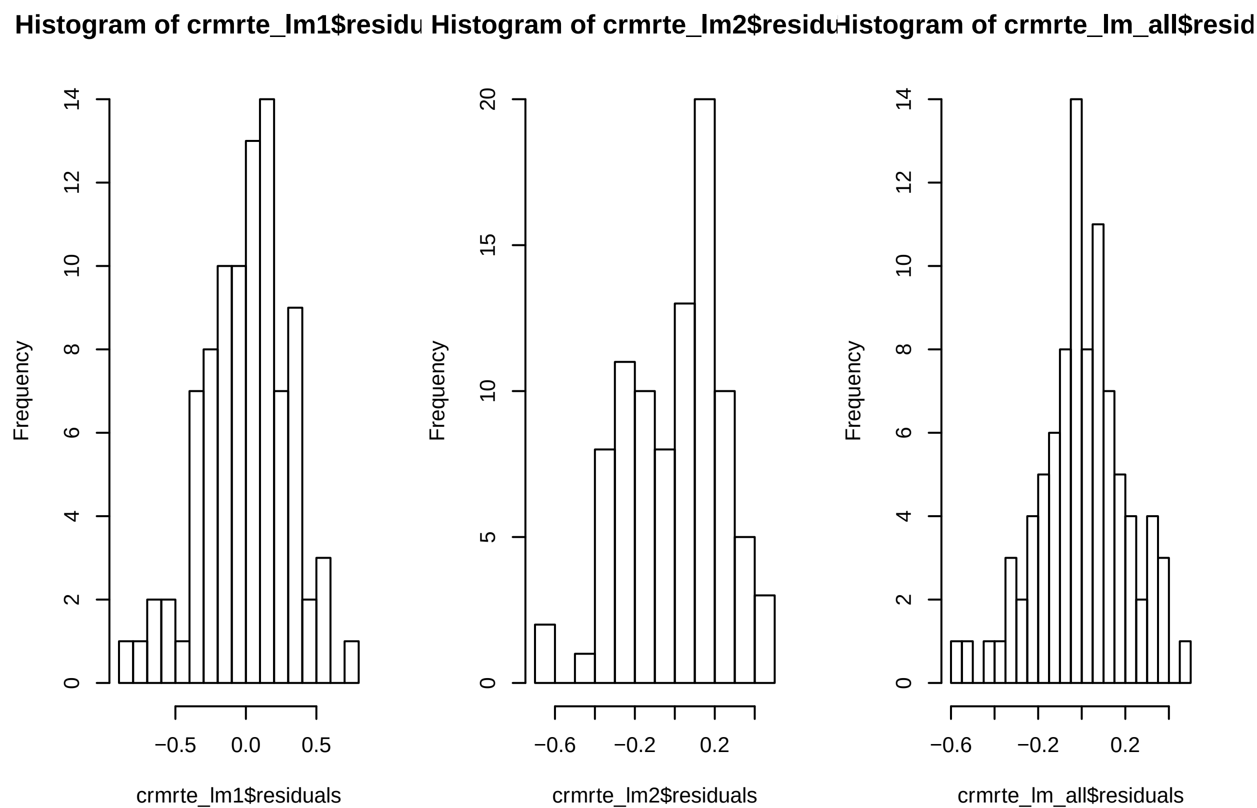

```r
par(mfrow=c(1,3))
plot(crmrte_lm1, which = 3)
plot(crmrte_lm2, which = 3)
plot(crmrte_lm_all, which = 3)
```




```
par(mfrow=c(1,3))
plot(crmrte_lm1, which = 5)
plot(crmrte_lm2, which = 5)
plot(crmrte_lm_all, which = 5)
```




```r
par(mfrow=c(1,3))
hist(crmrte_lm1$residuals, breaks = 15)
hist(crmrte_lm2$residuals, breaks = 15)
hist(crmrte_lm_all$residuals, breaks = 15)
```




```r
se.crmrte_lm1 <- sqrt(diag(vcovHC(crmrte_lm1)))
se.crmrte_lm2 <- sqrt(diag(vcovHC(crmrte_lm2)))
se.crmrte_lm_all <- sqrt(diag(vcovHC(crmrte_lm_all)))
stargazer(crmrte_lm1, crmrte_lm2,crmrte_lm_all,
          type = "text", omit.stat = "f",
          se = list(se.crmrte_lm1, se.crmrte_lm2, se.crmrte_lm_all),
          star.cutoffs = c(0.05, 0.01, 0.001))
```

```
##
## ===================================================================
##                                   Dependent variable:
##                     -----------------------------------------------
##                                       log(crmrte)
##                          (1)             (2)             (3)
## -------------------------------------------------------------------
## prbarr_imp                                            -1.705***
##                                                        (0.308)
##
## density               0.150***        0.103***         0.109*
##                        (0.026)         (0.026)         (0.052)
##
## taxpc.ln                                               -0.046
##                                                        (0.234)
##
## west                 -0.356***        -3.678*          -0.230
##                        (0.071)         (1.780)         (0.122)
```

```
##
## prbarr                    -1.269**          -1.404*
##                            (0.394)          (0.559)
##
## central                                                      -0.174*
##                                                              (0.078)
##
## urban                                                        -0.094
##                                                              (0.220)
##
## prbconv                   -0.552***        -0.566***        -0.666***
##                            (0.132)          (0.157)          (0.124)
##
## prbpris                                                      -0.135
##                                                              (0.432)
##
## avgsen                                                       -0.026
##                                                              (0.016)
##
## polpc_imp.ln                                0.655***         0.557**
##                                             (0.137)          (0.208)
##
## pctmin80                                     0.008**          0.008**
##                                             (0.003)          (0.003)
##
## west:polpc_imp.ln                           -0.539*
##                                             (0.274)
##
## wcon.ln                                                       0.343
##                                                              (0.243)
##
## wtuc.ln                                                       0.163
##                                                              (0.285)
##
## wtrd.ln                                                       0.250
##                                                              (0.306)
##
## wfir.ln                                                      -0.163
##                                                              (0.339)
##
## wser_imp.ln                                                  -0.498
##                                                              (0.307)
##
## wmfg.ln                                                      -0.039
##                                                              (0.164)
##
## wfed.ln                                                       0.694
##                                                              (0.433)
##
## wsta.ln                                                      -0.332
##                                                              (0.326)
##
## wloc.ln                                                       0.047
##                                                              (0.685)
```

```
##
## mix                                                    -0.656
##                                                        (0.559)
##
## pctymle                                                 2.089
##                                                        (1.307)
##
## Constant                -2.990***        1.129         -1.800
##                          (0.198)        (0.906)        (4.102)
##
## -------------------------------------------------------------------
## Observations               91              91             91
## R2                        0.691          0.811          0.864
## Adjusted R2               0.677          0.795          0.819
## Residual Std. Error 0.310 (df = 86) 0.247 (df = 83) 0.232 (df = 68)
## ===================================================================
## Note:                                 *p<0.05; **p<0.01; ***p<0.001
```