

w203_Lab3_group5_draft1: Joanna wang, Douglas(Zeliang) Xu

Part1: Looking at the data

This part is to look at the dataset in general to grow our understand of the data:

```
library(car)
```

```
## Loading required package: carData
```

```
data <- read.csv(file="crime_v2.csv", header=TRUE, sep=",",na.strings=c(``","","NA"))  
objects(data)
```

```
## [1] "avgsen"    "central"    "county"     "crmrte"     "density"    "mix"  
## [7] "pctmin80"  "pctymle"   "polpc"      "prbarr"     "prbconv"    "prbpris"  
## [13] "taxpc"     "urban"      "wcon"       "west"       "wfed"       "wfir"  
## [19] "wloc"      "wmfg"      "wser"       "wsta"       "wtrd"       "wtuc"  
## [25] "year"
```

```
summary(data)
```

```

##      county      year      crmrte      prbarr
## Min.   : 1.0   Min.   :87   Min.   :0.005533   Min.   :0.09277
## 1st Qu.: 52.0  1st Qu.:87   1st Qu.:0.020927  1st Qu.:0.20568
## Median :105.0  Median :87   Median :0.029986  Median :0.27095
## Mean    :101.6  Mean    :87   Mean    :0.033400  Mean    :0.29492
## 3rd Qu.:152.0  3rd Qu.:87   3rd Qu.:0.039642  3rd Qu.:0.34438
## Max.   :197.0  Max.   :87   Max.   :0.098966  Max.   :1.09091
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      prbconv      prbpris      avgsen      polpc
## Min.   :0.06838  Min.   :0.1500  Min.   : 5.380  Min.   :0.000746
## 1st Qu.:0.34541  1st Qu.:0.3648  1st Qu.: 7.340  1st Qu.:0.001231
## Median :0.45283  Median :0.4234  Median : 9.100  Median :0.001485
## Mean    :0.55128  Mean    :0.4108  Mean    : 9.647  Mean    :0.001702
## 3rd Qu.:0.58886  3rd Qu.:0.4568  3rd Qu.:11.420  3rd Qu.:0.001877
## Max.   :2.12121  Max.   :0.6000  Max.   :20.700  Max.   :0.009054
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      density      taxpc      west      central
## Min.   :0.00002  Min.   : 25.69  Min.   :0.0000  Min.   :0.0000
## 1st Qu.:0.54741  1st Qu.: 30.66  1st Qu.:0.0000  1st Qu.:0.0000
## Median :0.96226  Median : 34.87  Median :0.0000  Median :0.0000
## Mean    :1.42884  Mean    : 38.06  Mean    :0.2527  Mean    :0.3736
## 3rd Qu.:1.56824  3rd Qu.: 40.95  3rd Qu.:0.5000  3rd Qu.:1.0000
## Max.   :8.82765  Max.   :119.76  Max.   :1.0000  Max.   :1.0000
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      urban      pctmin80      wcon      wtuc
## Min.   :0.00000  Min.   : 1.284  Min.   :193.6  Min.   :187.6
## 1st Qu.:0.00000  1st Qu.: 9.845  1st Qu.:250.8  1st Qu.:374.6
## Median :0.00000  Median :24.312  Median :281.4  Median :406.5
## Mean    :0.08791  Mean    :25.495  Mean    :285.4  Mean    :411.7
## 3rd Qu.:0.00000  3rd Qu.:38.142  3rd Qu.:314.8  3rd Qu.:443.4
## Max.   :1.00000  Max.   :64.348  Max.   :436.8  Max.   :613.2
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      wtrd      wfir      wser      wmfq
## Min.   :154.2   Min.   :170.9   Min.   :133.0   Min.   :157.4
## 1st Qu.:190.9   1st Qu.:286.5   1st Qu.:229.7   1st Qu.:288.9
## Median :203.0   Median :317.3   Median :253.2   Median :320.2
## Mean    :211.6   Mean    :322.1   Mean    :275.6   Mean    :335.6
## 3rd Qu.:225.1   3rd Qu.:345.4   3rd Qu.:280.5   3rd Qu.:359.6
## Max.   :354.7   Max.   :509.5   Max.   :2177.1  Max.   :646.9
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      wfed      wsta      wloc      mix
## Min.   :326.1   Min.   :258.3   Min.   :239.2   Min.   :0.01961
## 1st Qu.:400.2   1st Qu.:329.3   1st Qu.:297.3   1st Qu.:0.08074
## Median :449.8   Median :357.7   Median :308.1   Median :0.10186
## Mean    :442.9   Mean    :357.5   Mean    :312.7   Mean    :0.12884
## 3rd Qu.:478.0   3rd Qu.:382.6   3rd Qu.:329.2   3rd Qu.:0.15175
## Max.   :598.0   Max.   :499.6   Max.   :388.1   Max.   :0.46512
## NA's    :6     NA's    :6     NA's    :6       NA's    :6
##      pctymle
## Min.   :0.06216
## 1st Qu.:0.07443
## Median :0.07771
## Mean    :0.08396

```

```
## 3rd Qu.:0.08350
## Max.    :0.24871
## NA's     :6
```

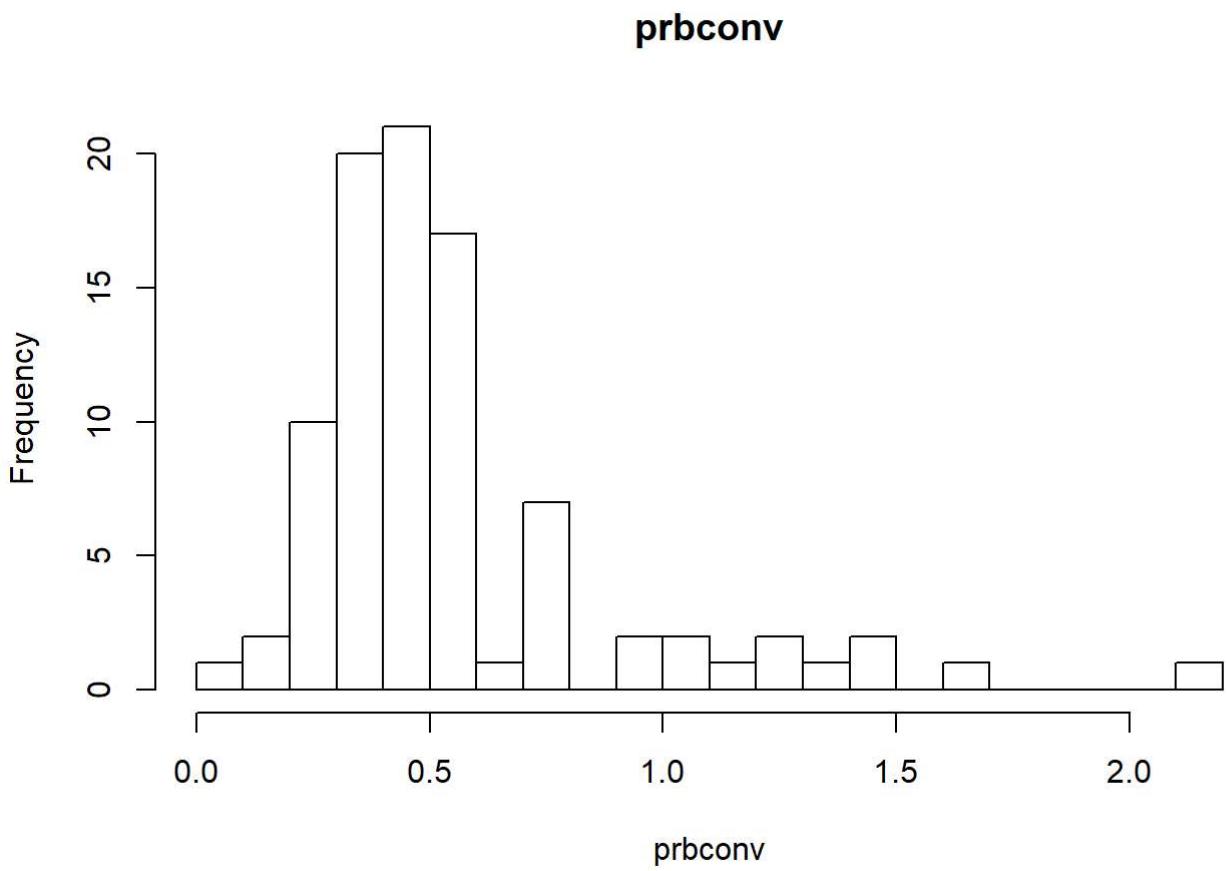
```
tail(data,11)
```

```

##    county year    crmrte   prbarr   prbconv   prbpris avgsen      polpc
## 87     191   87 0.0458895 0.172257 0.450000 0.421053    9.59 0.00122733
## 88     193   87 0.0235277 0.266055 0.588859 0.423423    5.86 0.00117887
## 89     193   87 0.0235277 0.266055 0.588859 0.423423    5.86 0.00117887
## 90     195   87 0.0313973 0.201397 1.670520 0.470588  13.02 0.00445923
## 91     197   87 0.0141928 0.207595 1.182930 0.360825  12.23 0.00118573
## 92     NA     NA     NA     NA     NA     NA     NA     NA
## 93     NA     NA     NA     NA     NA     NA     NA     NA
## 94     NA     NA     NA     NA     NA     NA     NA     NA
## 95     NA     NA     NA     NA     NA     NA     NA     NA
## 96     NA     NA     NA     NA     NA     NA     NA     NA
## 97     NA     NA     NA     NA     NA     NA     NA     NA
##      density    taxpc west central urban pctmin80      wcon      wtuc
## 87 1.7725632 32.74533    0      0      0 34.42830 318.0599 400.8570
## 88 0.8138298 28.51783    1      0      0 5.93109 285.8289 480.1948
## 89 0.8138298 28.51783    1      0      0 5.93109 285.8289 480.1948
## 90 1.7459893 53.66693    0      0      0 37.43110 315.1641 377.9356
## 91 0.8898810 25.95258    1      0      0 5.46081 314.1660 341.8803
## 92     NA     NA     NA     NA     NA     NA     NA     NA
## 93     NA     NA     NA     NA     NA     NA     NA     NA
## 94     NA     NA     NA     NA     NA     NA     NA     NA
## 95     NA     NA     NA     NA     NA     NA     NA     NA
## 96     NA     NA     NA     NA     NA     NA     NA     NA
## 97     NA     NA     NA     NA     NA     NA     NA     NA
##      wtrd      wfir      wser      wmgf      wfed      wsta      wloc      mix
## 87 230.9888 320.0345 238.4958 295.26 334.55 375.45 327.62 0.08616445
## 88 268.3836 365.0196 295.9352 295.63 468.26 337.88 348.74 0.11050157
## 89 268.3836 365.0196 295.9352 295.63 468.26 337.88 348.74 0.11050157
## 90 246.0614 411.4330 296.8684 392.27 480.79 303.11 337.28 0.15612382
## 91 182.8020 348.1432 212.8205 322.92 391.72 385.65 306.85 0.06756757
## 92     NA     NA     NA     NA     NA     NA     NA     NA
## 93     NA     NA     NA     NA     NA     NA     NA     NA
## 94     NA     NA     NA     NA     NA     NA     NA     NA
## 95     NA     NA     NA     NA     NA     NA     NA     NA
## 96     NA     NA     NA     NA     NA     NA     NA     NA
## 97     NA     NA     NA     NA     NA     NA     NA     NA
##      pctymle
## 87 0.08828809
## 88 0.07819394
## 89 0.07819394
## 90 0.07945071
## 91 0.07419893
## 92     NA
## 93     NA
## 94     NA
## 95     NA
## 96     NA
## 97     NA

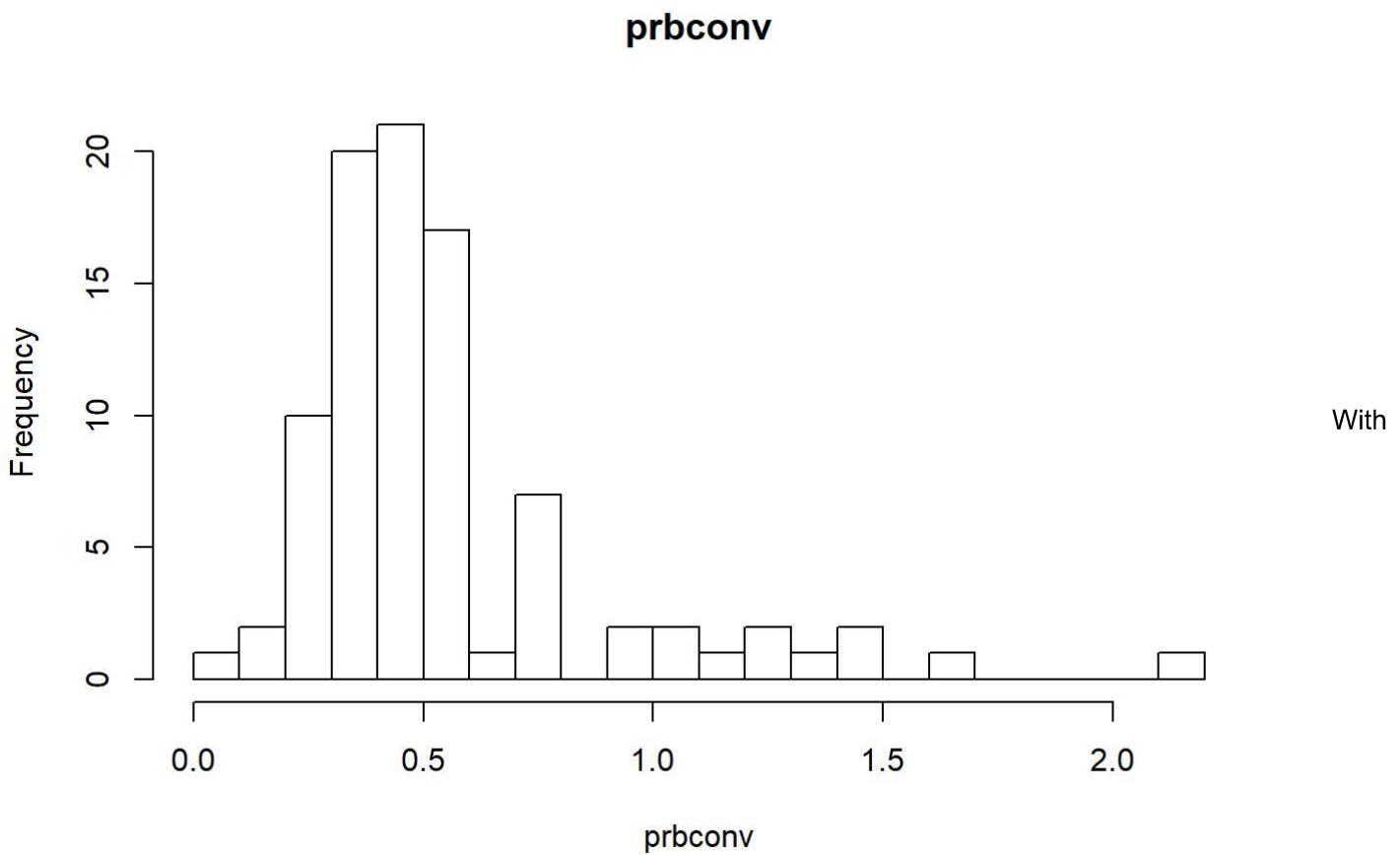
```

```
hist(data$prbconv, breaks=20, main="prbconv", xlab="prbconv")
```



Some of the things we see in the dataset: 1. 6 NA 2. take out year column 3. "prbarr" max > 1 4. "prbconv" strange characters and blank spaces; also the probability is bigger than 1 5. taxpc, what is the unit, what does it mean? Outlier at 119. Is the unit %? 6. pctmin80 data is too old 7. 15-23: different industry avg. wages 8. 24 mix: ratio of face-to-face crime 9. percentage young male (what is the age:15-24)

```
hist(data$prbconv, breaks=20, main="prbconv", xlab="prbconv")
```



the import method modified, we are able to address the missing values and the special character error in the *prbconv* data column

Data Cleaning

1. remove NA

```
data <- na.omit(data)
summary(data)
```

```

##      county      year      crmrte      prbarr
## Min.   : 1.0   Min.   :87   Min.   :0.005533   Min.   :0.09277
## 1st Qu.: 52.0  1st Qu.:87   1st Qu.:0.020927  1st Qu.:0.20568
## Median :105.0  Median :87   Median :0.029986  Median :0.27095
## Mean    :101.6  Mean    :87   Mean    :0.033400  Mean    :0.29492
## 3rd Qu.:152.0  3rd Qu.:87   3rd Qu.:0.039642  3rd Qu.:0.34438
## Max.   :197.0   Max.   :87   Max.   :0.098966  Max.   :1.09091
##      prbconv      prbpris      avgsen      polpc
## Min.   :0.06838  Min.   :0.1500  Min.   : 5.380  Min.   :0.0007459
## 1st Qu.:0.34541  1st Qu.:0.3648  1st Qu.: 7.340  1st Qu.:0.0012308
## Median :0.45283  Median :0.4234  Median : 9.100  Median :0.0014853
## Mean    :0.55128  Mean    :0.4108  Mean    : 9.647  Mean    :0.0017022
## 3rd Qu.:0.58886  3rd Qu.:0.4568  3rd Qu.:11.420  3rd Qu.:0.0018768
## Max.   :2.12121  Max.   :0.6000  Max.   :20.700  Max.   :0.0090543
##      density      taxpc      west      central
## Min.   :0.00002  Min.   : 25.69  Min.   :0.0000  Min.   :0.0000
## 1st Qu.:0.54741  1st Qu.: 30.66  1st Qu.:0.0000  1st Qu.:0.0000
## Median :0.96226  Median : 34.87  Median :0.0000  Median :0.0000
## Mean    :1.42884  Mean    : 38.06  Mean    :0.2527  Mean    :0.3736
## 3rd Qu.:1.56824  3rd Qu.: 40.95  3rd Qu.:0.5000  3rd Qu.:1.0000
## Max.   :8.82765  Max.   :119.76  Max.   :1.0000  Max.   :1.0000
##      urban      pctmin80      wcon      wtuc
## Min.   :0.00000  Min.   : 1.284  Min.   :193.6  Min.   :187.6
## 1st Qu.:0.00000  1st Qu.: 9.845  1st Qu.:250.8  1st Qu.:374.6
## Median :0.00000  Median :24.312  Median :281.4  Median :406.5
## Mean    :0.08791  Mean    :25.495  Mean    :285.4  Mean    :411.7
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## Max.   :1.00000  Max.   :64.348  Max.   :436.8  Max.   :613.2
##      wtrd      wfir      wser      wmgf
## Min.   :154.2   Min.   :170.9   Min.   :133.0   Min.   :157.4
## 1st Qu.:190.9   1st Qu.:286.5   1st Qu.:229.7   1st Qu.:288.9
## Median :203.0   Median :317.3   Median :253.2   Median :320.2
## Mean    :211.6   Mean    :322.1   Mean    :275.6   Mean    :335.6
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## Max.   :354.7   Max.   :509.5   Max.   :2177.1  Max.   :646.9
##      wfed      wsta      wloc      mix
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## Max.   :598.0   Max.   :499.6   Max.   :388.1   Max.   :0.46512
##      pctymle
## Min.   :0.06216
## 1st Qu.:0.07443
## Median :0.07771
## Mean    :0.08396
## 3rd Qu.:0.08350
## Max.   :0.24871

```

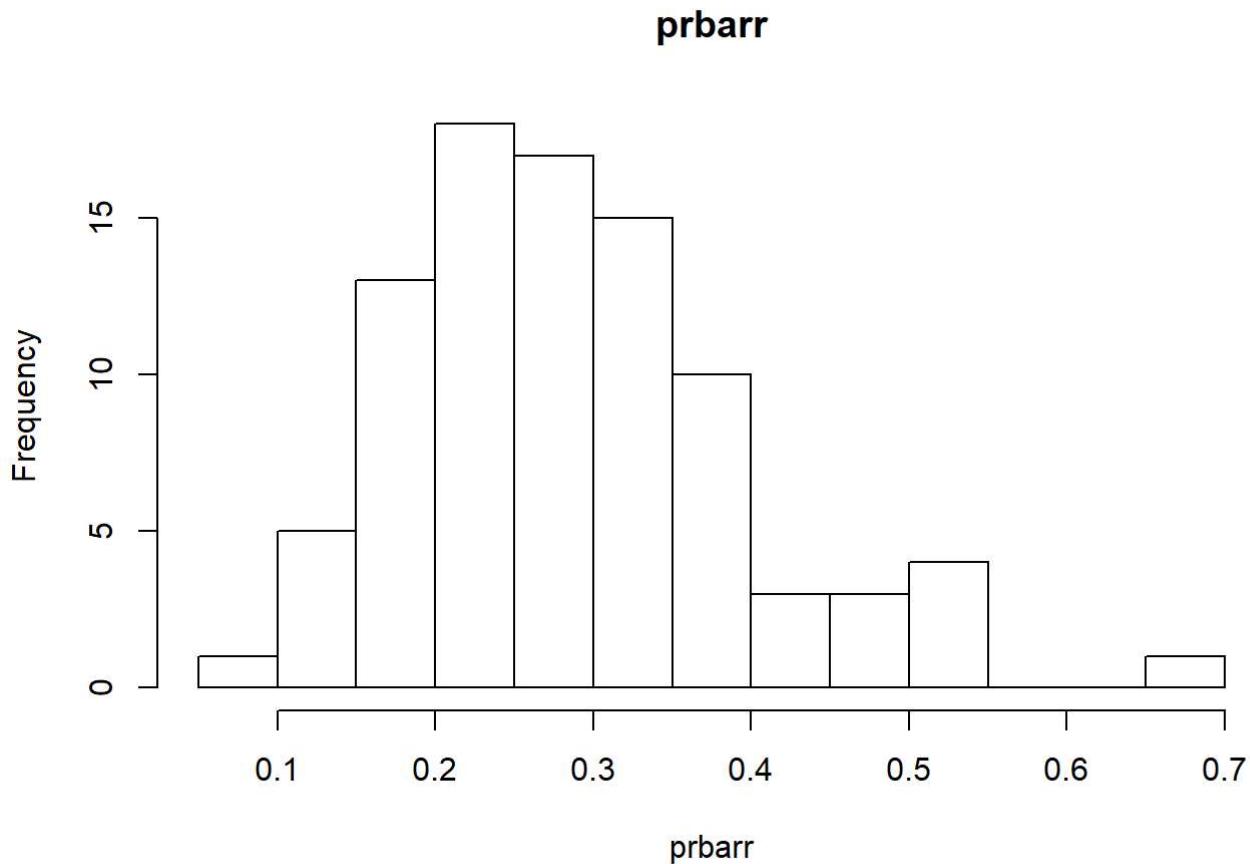
2. take out year column as it does not mean anything in our analysis

```
data_clean <- subset(data, select=-c(year))
objects(data_clean)
```

```
## [1] "avgsen"    "central"    "county"     "crmrte"     "density"    "mix"
## [7] "pctmin80"   "pctymle"    "polpc"      "prbarr"     "prbconv"    "prbpris"
## [13] "taxpc"      "urban"       "wcon"       "west"       "wfed"       "wfir"
## [19] "wloc"       "wmfg"       "wser"       "wsta"       "wtrd"       "wtuc"
```

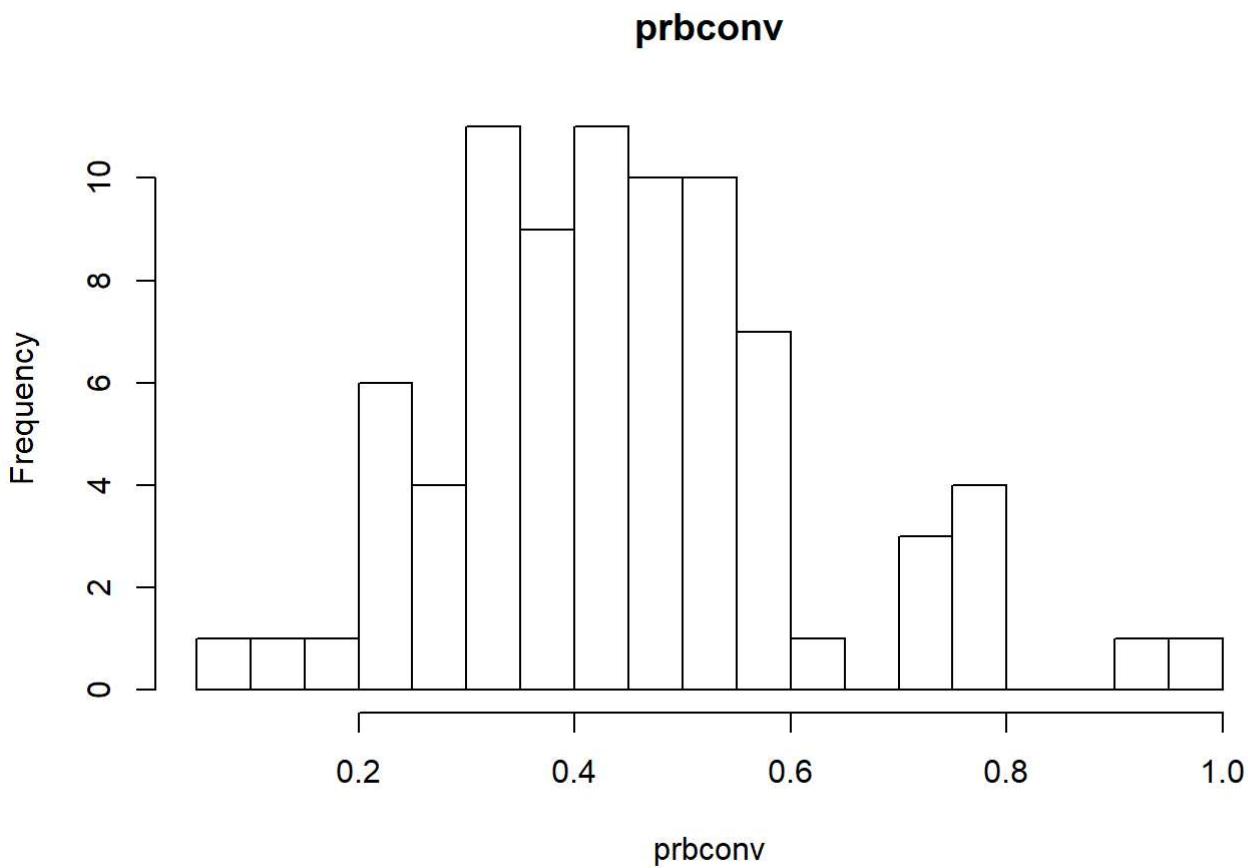
3. "prbarr" max > 1

```
data_clean <- subset(data_clean, data_clean$prbarr < 1)
hist(data_clean$prbarr, breaks=20, main="prbarr", xlab="prbarr")
```



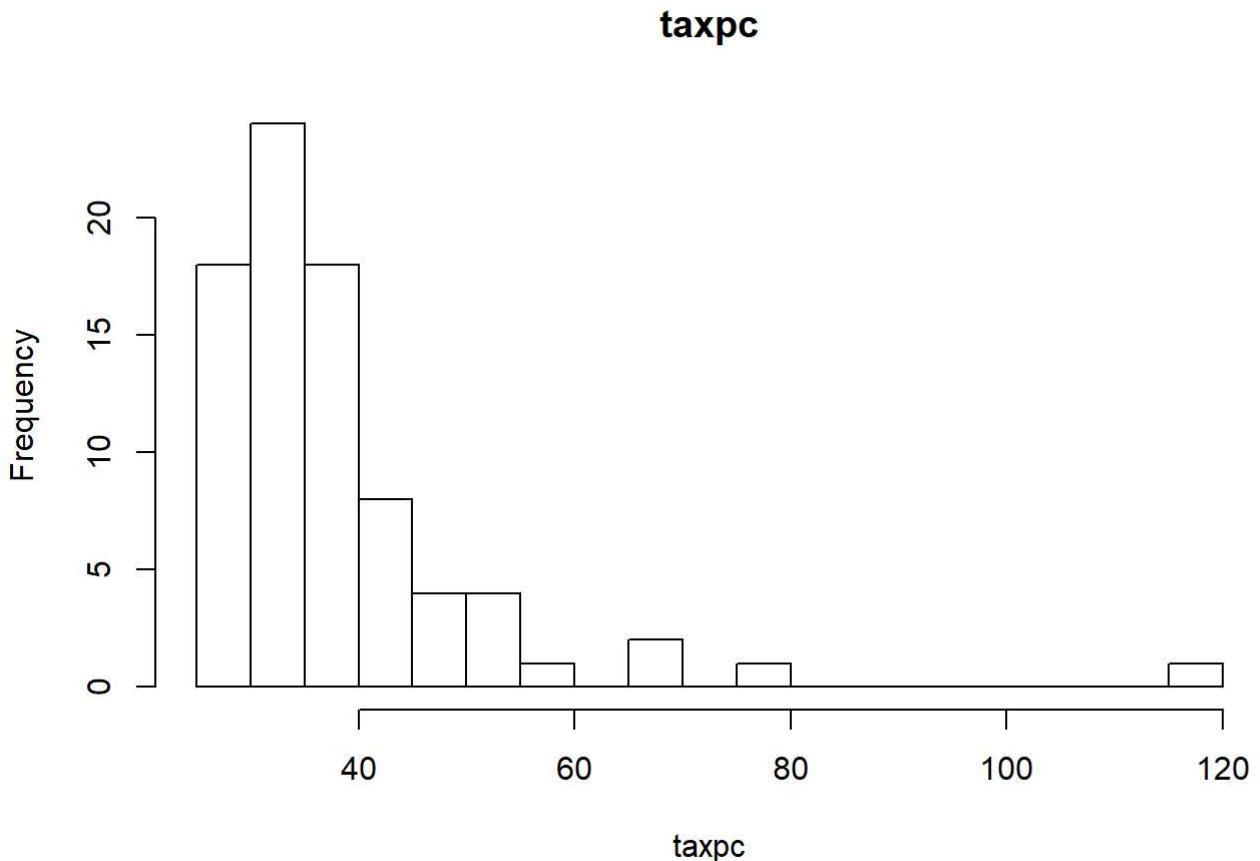
"prbconv" strange characters and blank spaces; also the probability is bigger than 1
blank space and strange characters are taken care of in data import

```
data_clean <- subset(data_clean, data_clean$prbconv < 1)
hist(data_clean$prbconv, breaks=20, main="prbconv", xlab="prbconv")
```



taxpc: There seems to be some anomaly that is very far apart from other data points, but we have no evidence to say whether the data has anomaly or not. It could be an error or it could just be that the county has high tax per capita

```
hist(data_clean$taxpc, breaks=20, main="taxpc", xlab="taxpc")
```



over-paid service industry: we found that the maximum value of the avg. weekly wage of service industry is above 2000, which is way more than the other industries. Based on the background knowledge, we don't believe there should be significant difference between the service industry and other industries in terms of compensation difference, and the data point above 2000 should be an error in the data, and we decided to remove them

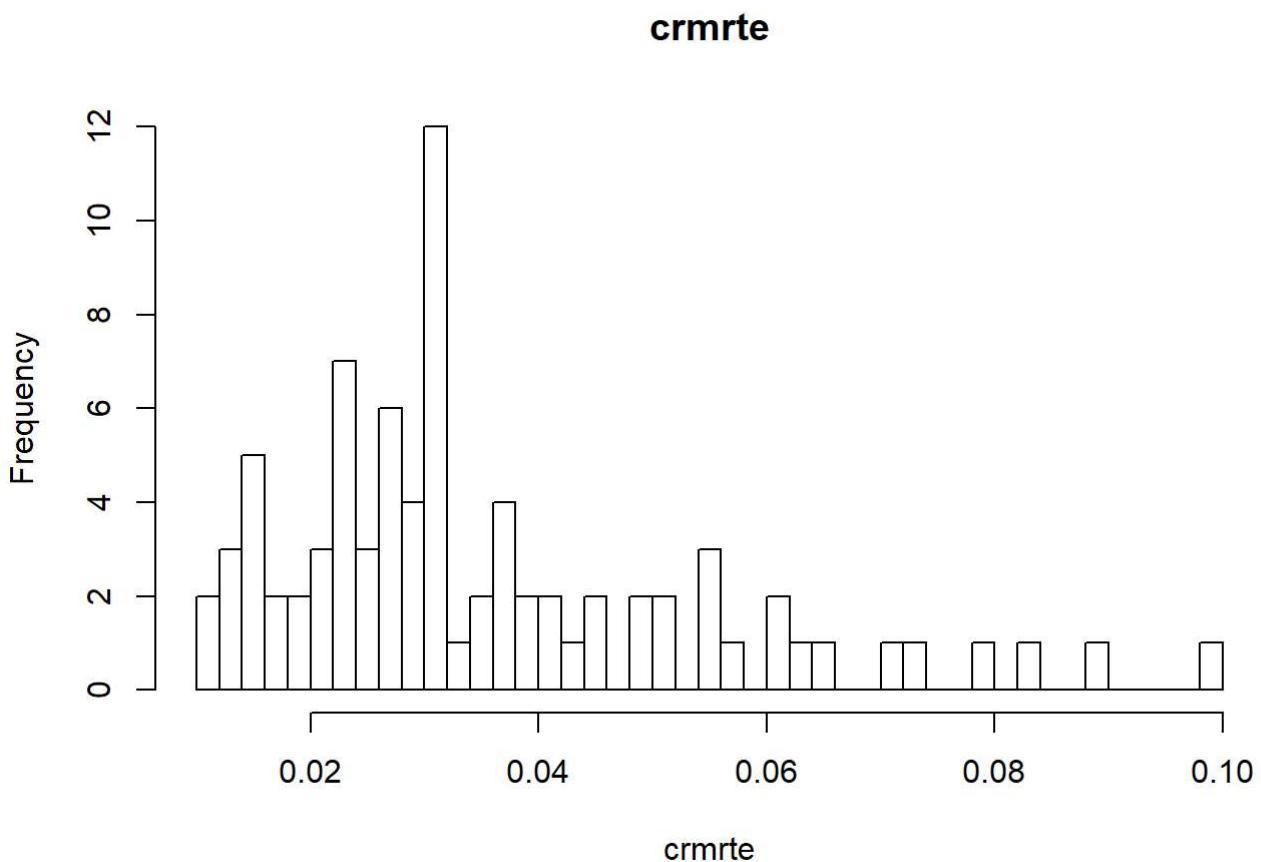
```
data_clean <- subset(data_clean, data_clean$wser<1000)
summary(data_clean$wser)
```

```
##      Min. 1st Qu. Median    Mean 3rd Qu.    Max.
##  133.0   230.3  253.6  255.2  278.1  391.3
```

EDA

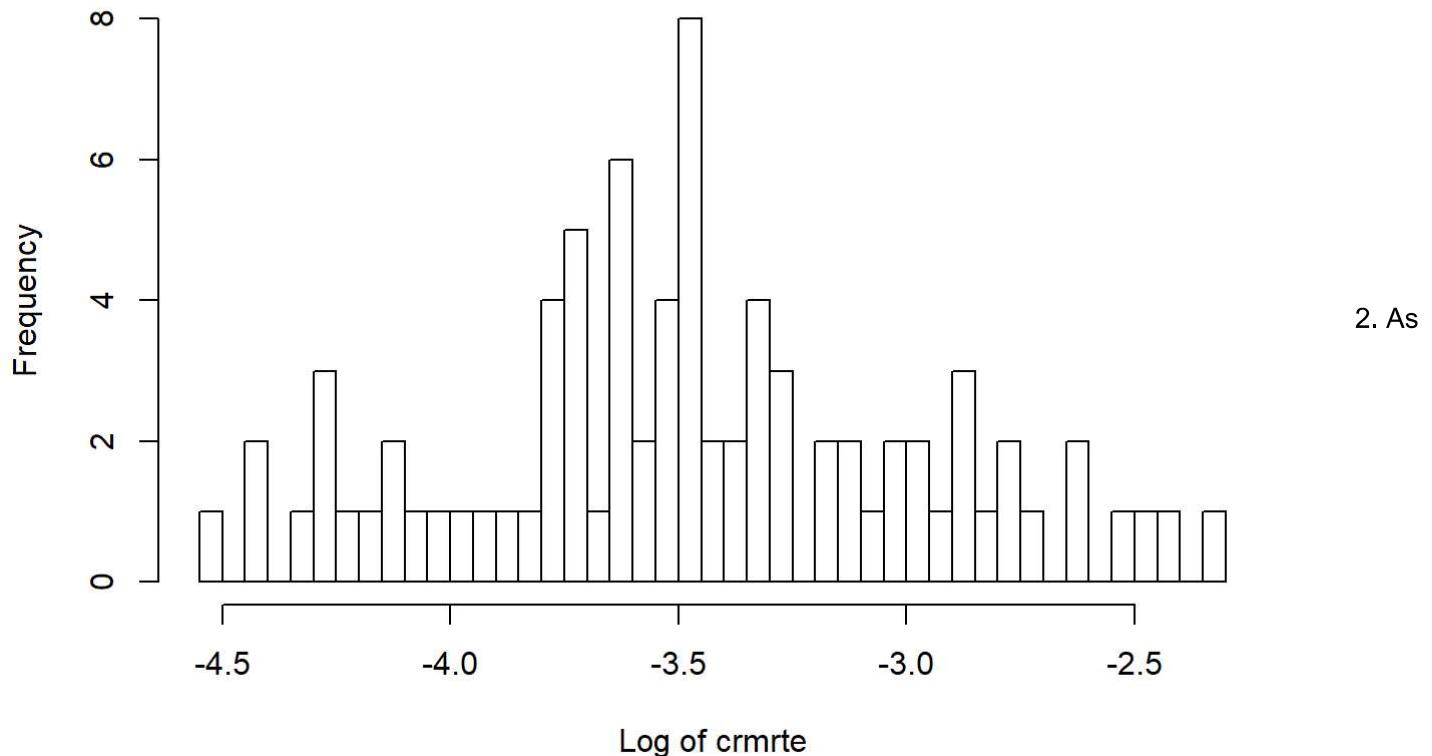
- As the first part of the data analysis, we are taking a look at the distributions of the dependent variable:

```
hist(data_clean$crrmrte, breaks=50, main="crrmrte", xlab="crrmrte")
```



```
hist(log(data_clean$crmrte),breaks=50, main="Log transform of crmrte", xlab="Log of crmrte")
```

Log transform of crmrte

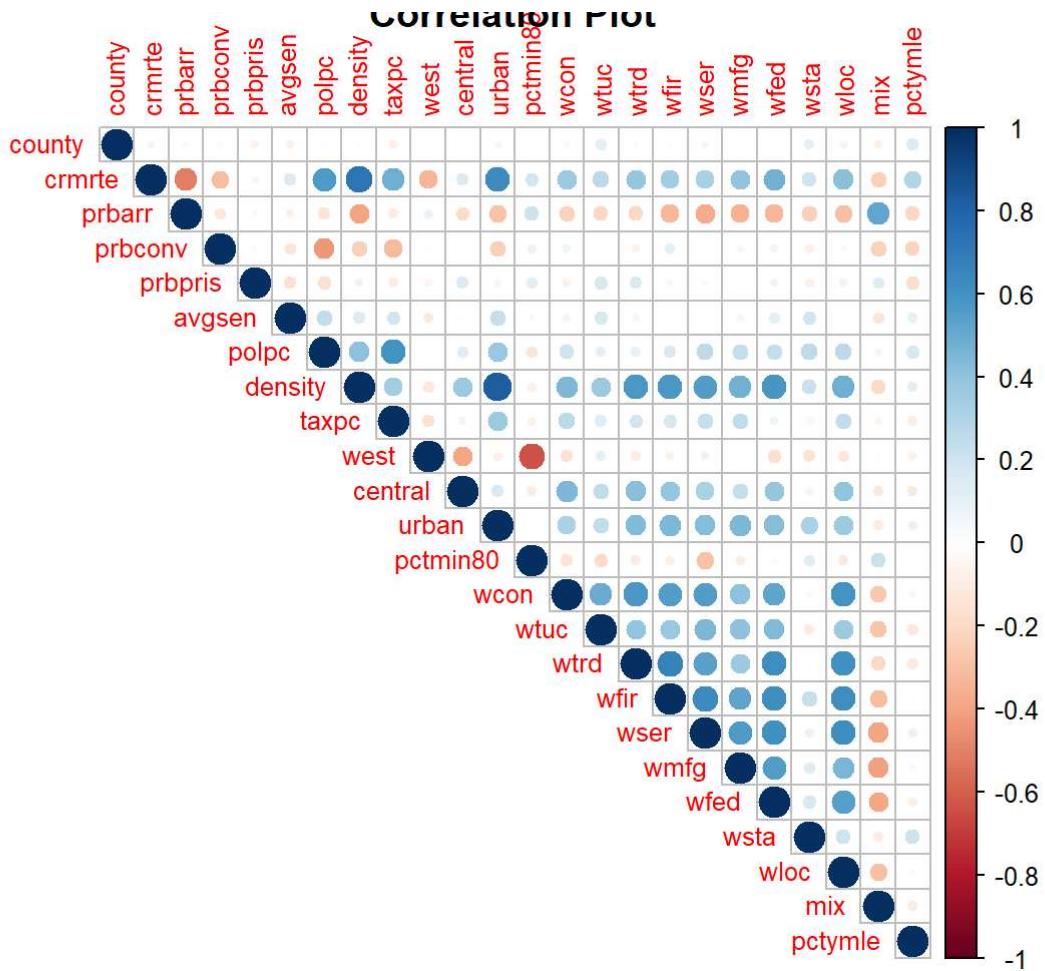


the second part of the EDA, we take an initial look at the simple correlation between each variable inside the dataframe to help us understand the general correlations between each variable and the dependent variable to help identify the explanatory variables of interest

```
# correlation plot
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
corrplot(cor(data_clean[,sapply(data_clean,is.numeric)]),is.corr=T, method = "circle", type='upper',main = "Correlation Plot", tl.cex=0.8)
```



Research Question

After the initial data cleaning and data analysis, we have defined our research question to be: how to reduce crime rate within North Carolina, and especially what are the most effective measures in reducing crime rate that might have been neglected before.

The question is asked to help the political campaign to propose effective strategies to reduce crime rate, especially in the area that might have been neglected before. From the simple correlation plot, we found that variable *mix* has strong positive correlation with *prbarr*. It can make sense because face-to-face crimes are more severe and usually have more police concentration and resources that lead to higher probability of arrest. However, it might not be very easy for non face-to-face crime, which is still the majority of crimes that happened, but actually seem to have pretty low arrest rate. This conclusion can be obtained by the fact that crime rate (*crmrte*) is negatively correlated with probability of arrest(*prbarr*) while percentage of face-to-face crime (*mix*) is positively correlated with probability of arrest (*prbarr*). Therefore, how to increase *prbarr* for non face-to-face crime is really the strategy we need to focus our energy on.

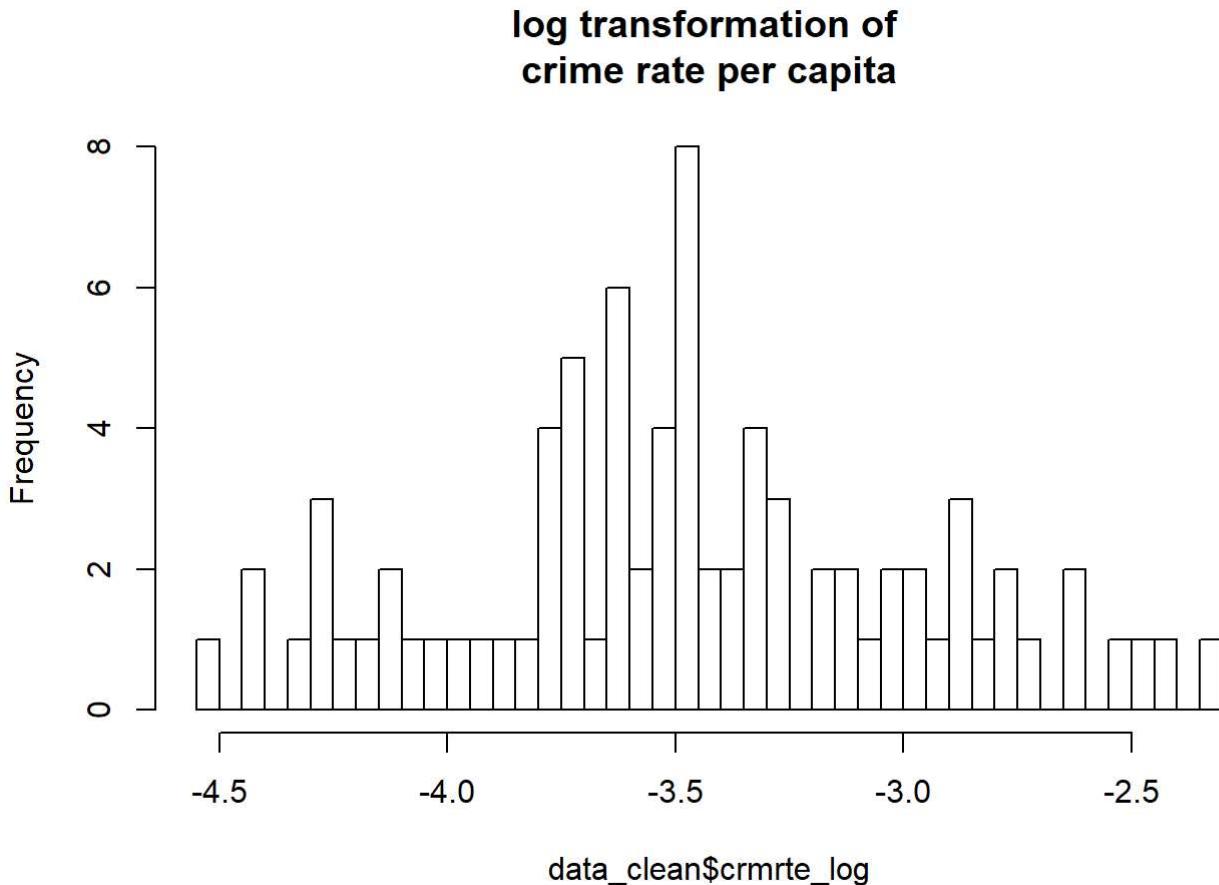
Fitting model 1

model 1: $\$crmrte = _0 + _1 * prbarr + _2 * prbconv + _3 * avgsen + _4 * prbpris + u \$$

Based on the understanding of what each parameter stands for, we have chosen *crmrte* as the only dependent variable to use for our analysis. The variable is a direct indicator of average crime committed to North Carolina counties. To start with, we took a look at the distribution of the dataset.

From the analysis of the EDA, the distribution of crmrte does not look particularly normal, but the log transformed crmrte looks much more normally distributed. To reduce the standard error in the model building process, we decided that in our model fitting, we are going to use the log transformed *crmrte* as our dependent variable. That being said, we are creating another variable that indicates the log transformed *crmrte*

```
data_clean$crmrte_log <- log(data_clean$crmrte)
hist(data_clean$crmrte_log, breaks=50, main="log transformation of
crime rate per capita")
```

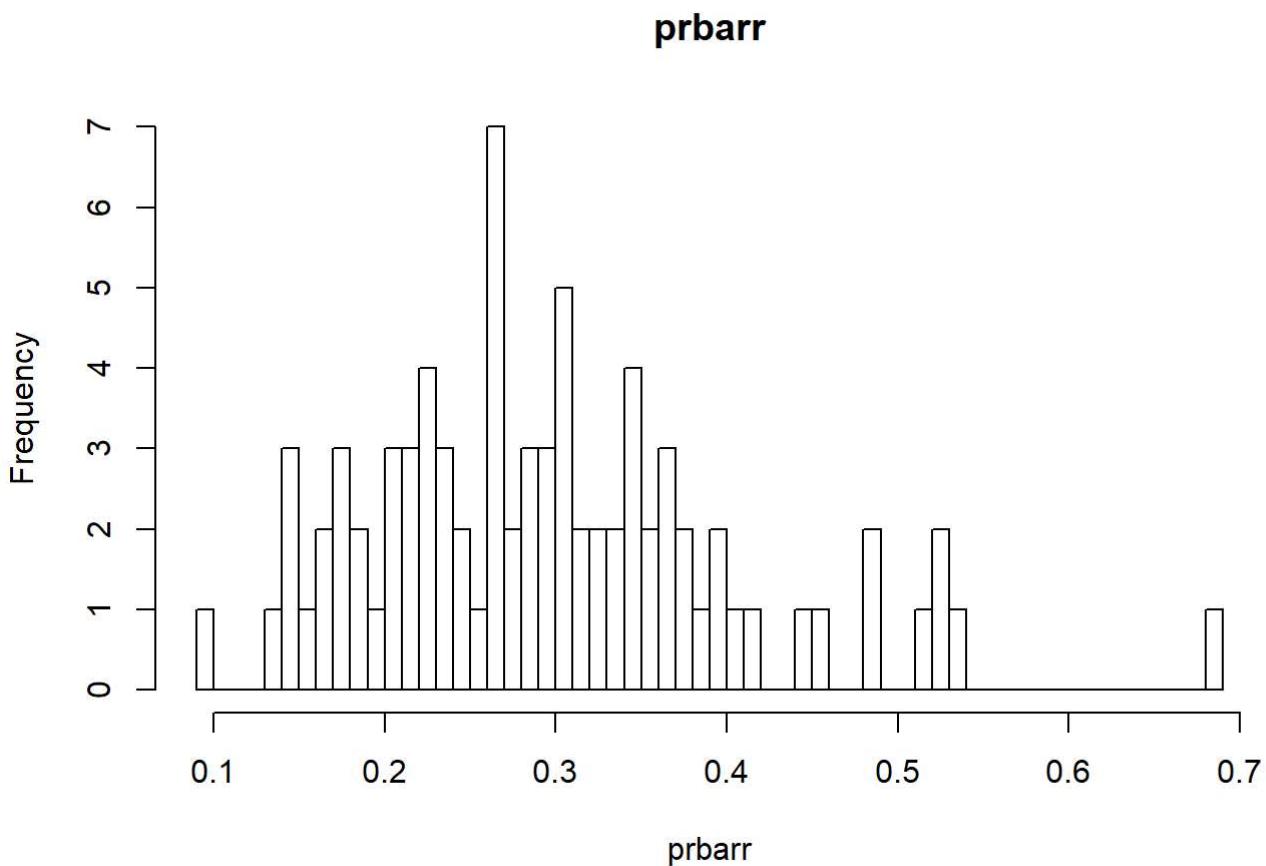


Looking at the other variables, and the simple correlation plot in initial EDA, we are proposing the explanatory variables that we believe contribute to crime rate:

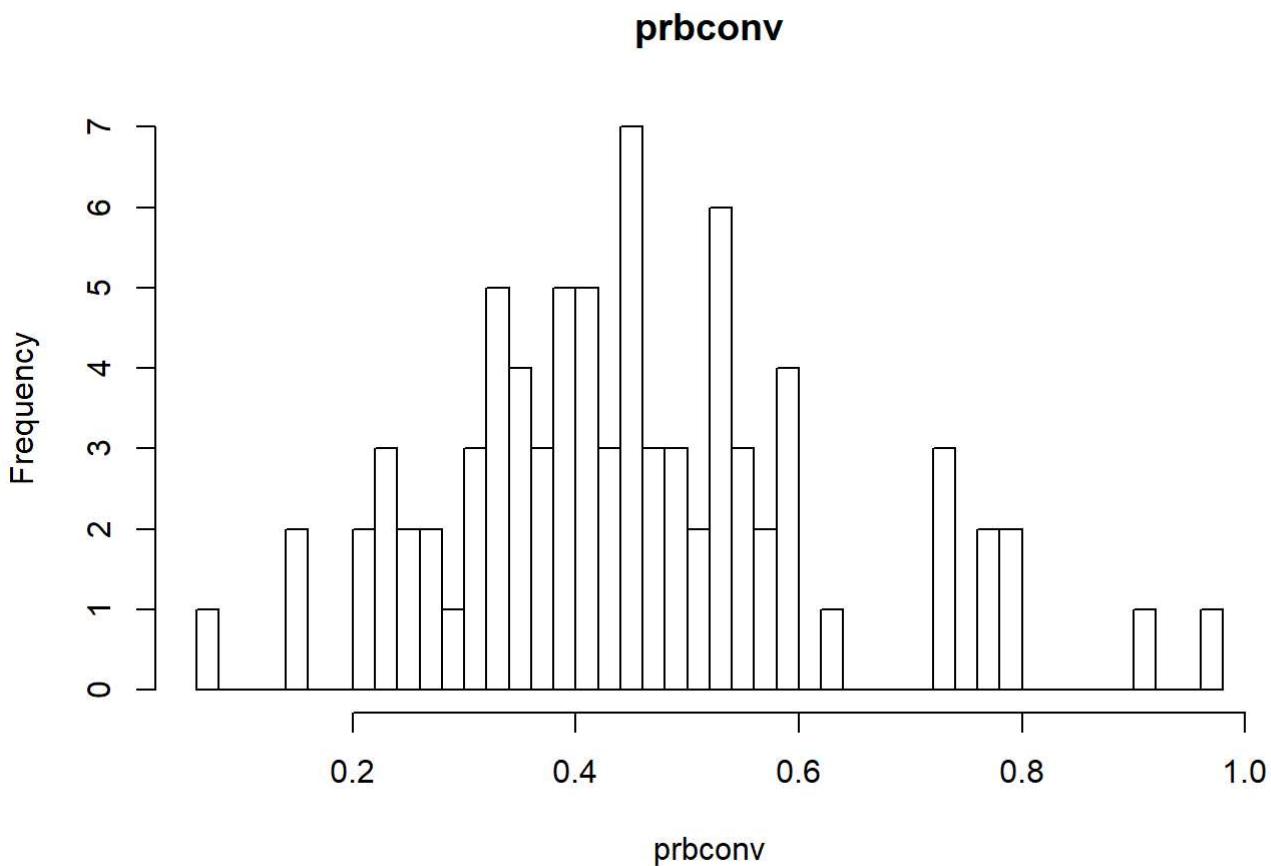
1. prbarr: the probability of arrest should be a direct contributing factor to crime rate. In other words, if people who have potential to commit a crime believe the chance of them getting arrested is small, then it might encourage them to commit a crime
2. prbconv: after getting arrested, getting suspects convicted are the only way to let them take the punishment they deserve.
3. prbpris
4. avgsen: both probability of prison sentence reflect the severity of the punishment, which should directly impact the crime rate

With the above being proposed, we decided to take a look at the distribution of each explanatory variable:

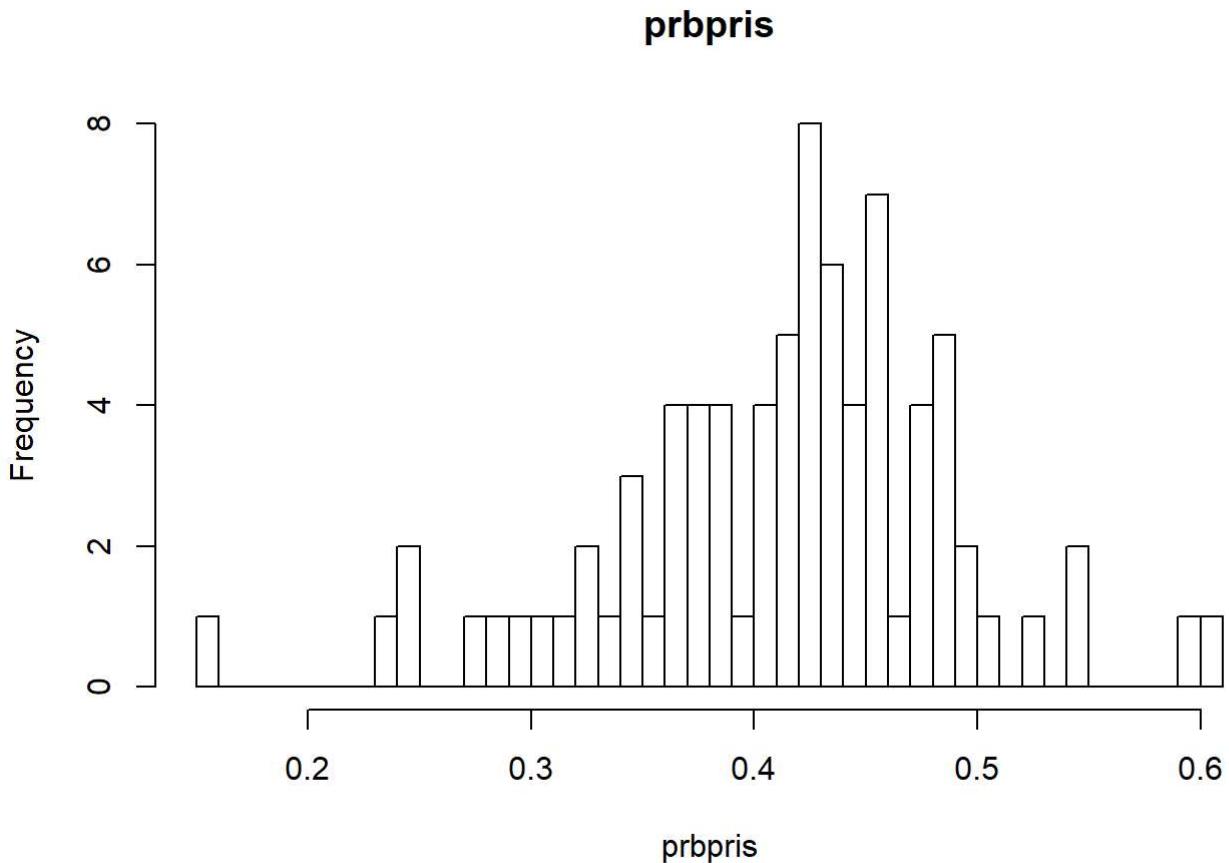
```
# prbarr
hist(data_clean$prbarr,breaks=50,main="prbarr", xlab="prbarr")
```



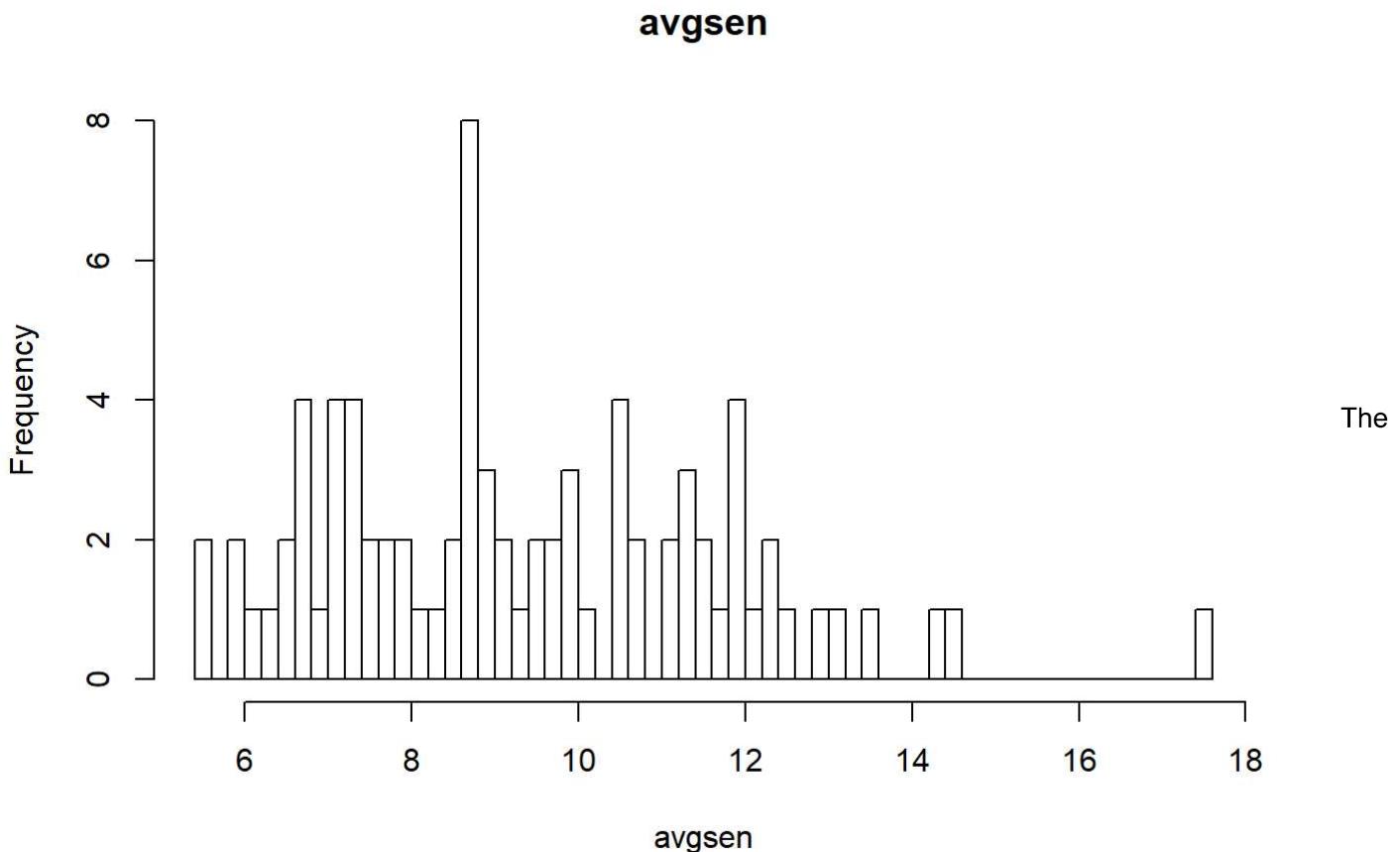
```
#prbconv  
hist(data_clean$prbconv, breaks=50, main="prbconv", xlab="prbconv")
```



```
#prbpris  
hist(data_clean$prbpris, breaks=50, main="prbpris", xlab="prbpris")
```



```
#avgsen  
hist(data_clean$avgsen, breaks=50, main="avgsen", xlab="avgsen")
```

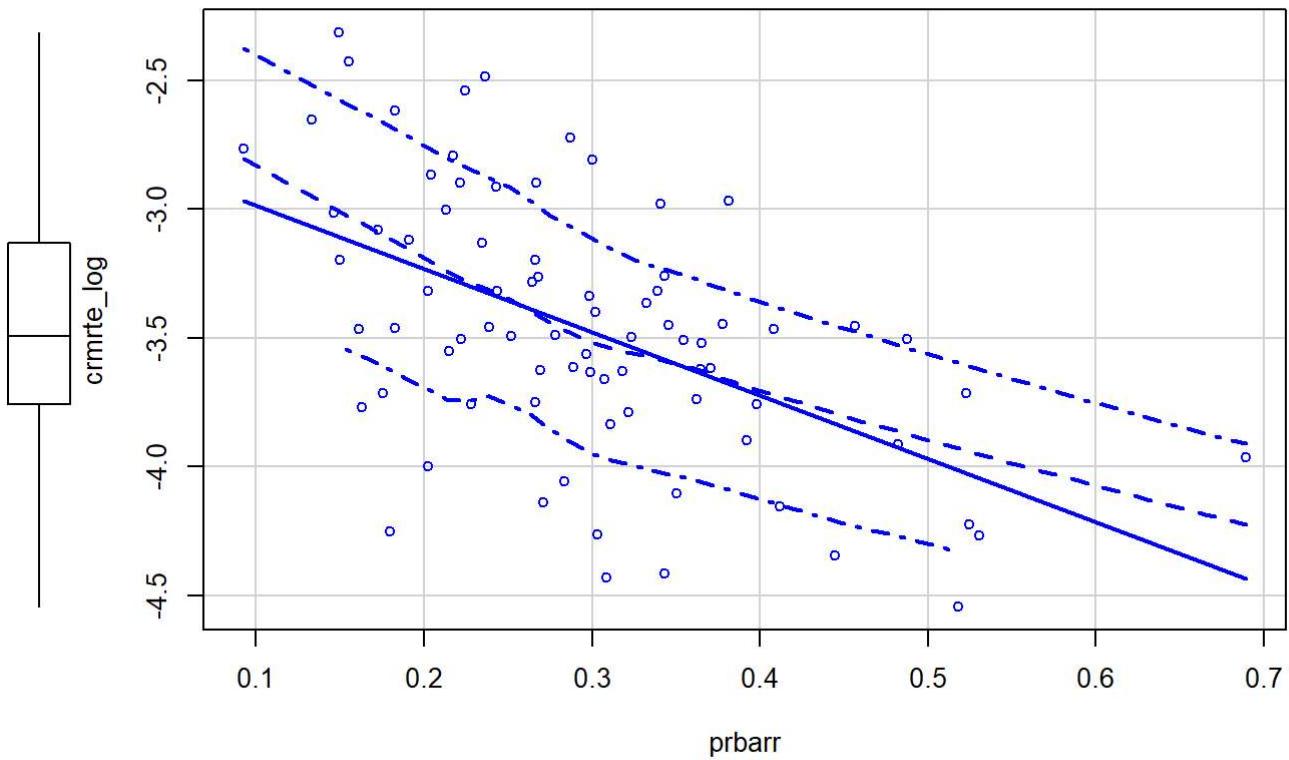


above histograms of each explanatory variable all seem rather normally distributed, with some anomalies implied in *prbarr* and *avgsen*. However, we don't think there is enough evidence to make a decision on whether the data is anomaly or not, and we will use the data for model building.

Next, we want to look at the scatterplot between each key explanatory variable and the dependent variable to decide on model specification:

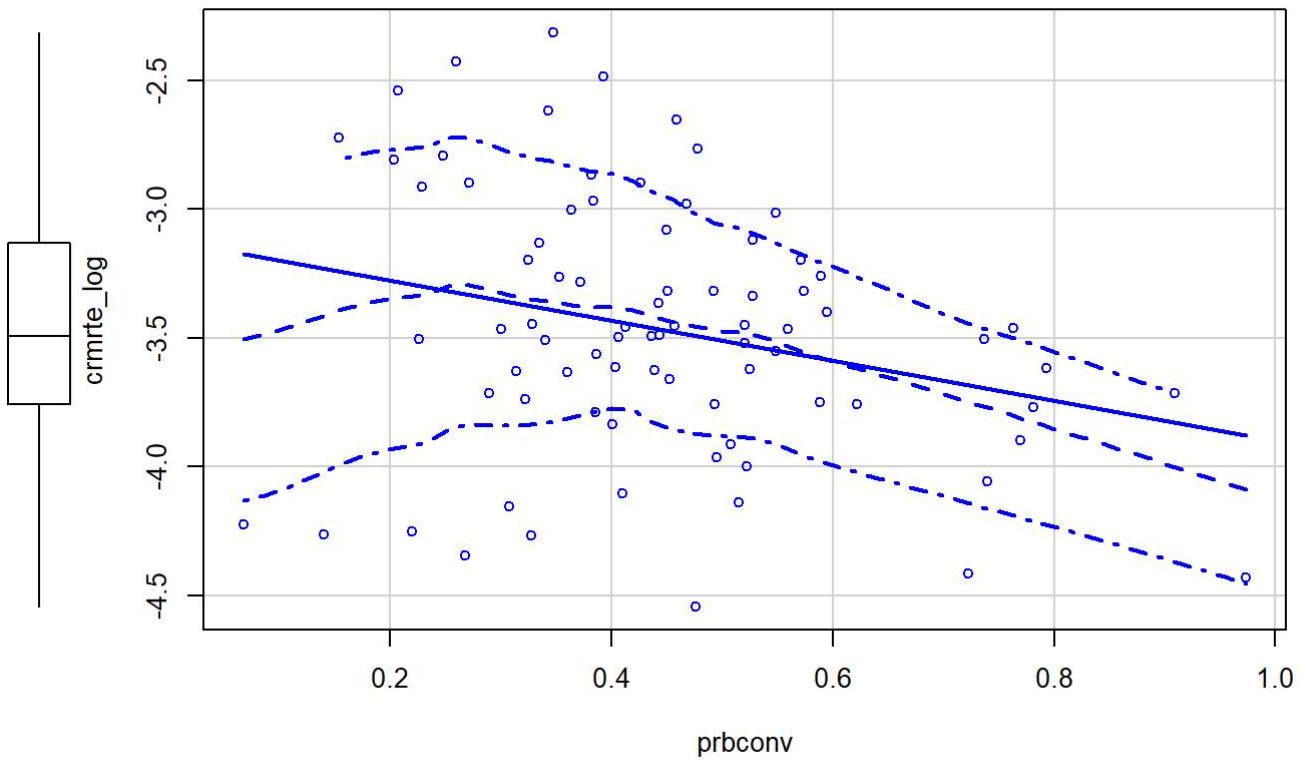
```
scatterplot(data_clean$prbarr,data_clean$crrmrte_log, main="prbarr vs. crrmrte_log", xlab="prbarr",
, ylab="crrmrte_log")
```

prbarr vs. crmrte_log



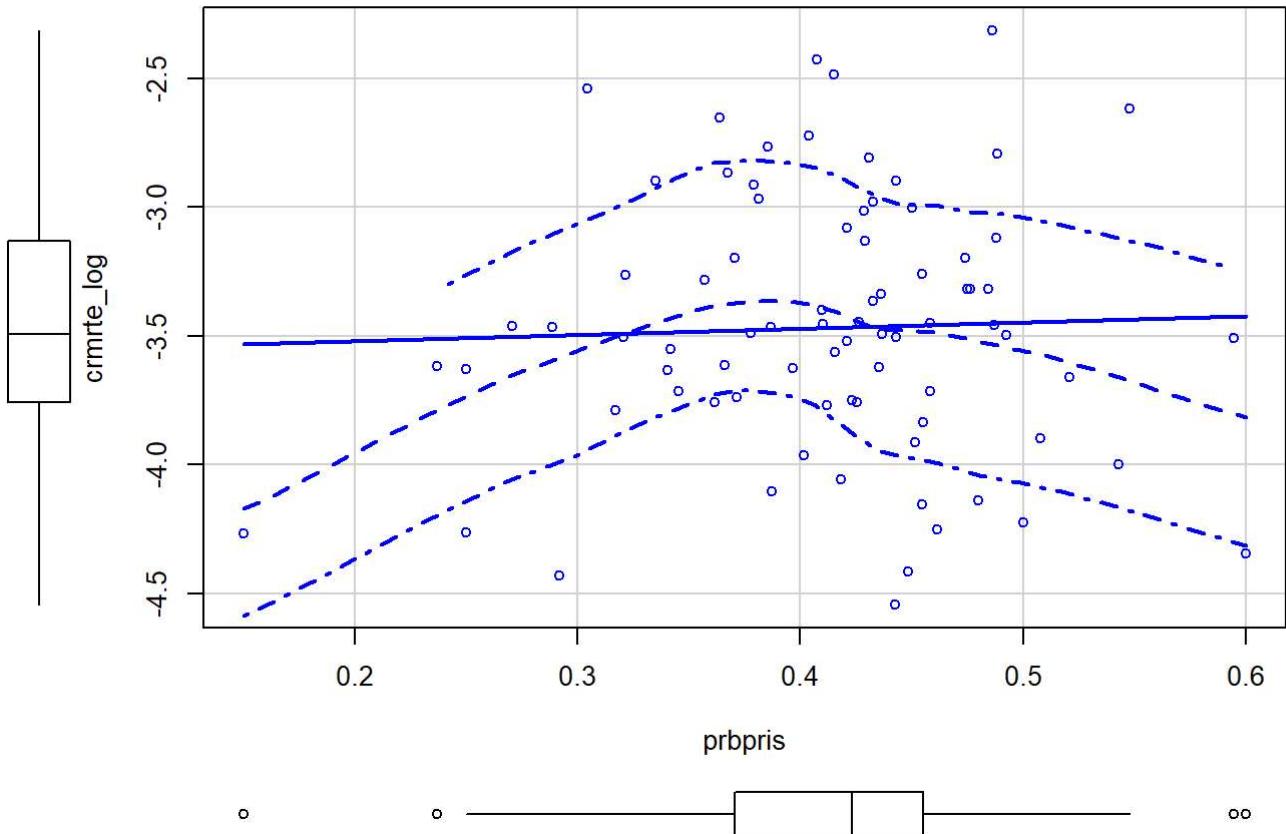
```
scatterplot(data_clean$prbconv,data_clean$crmrte_log, main="prbconv vs. crmrte_log", xlab="prbco  
nv", ylab="crmrte_log")
```

prbconv vs. crmrte_log

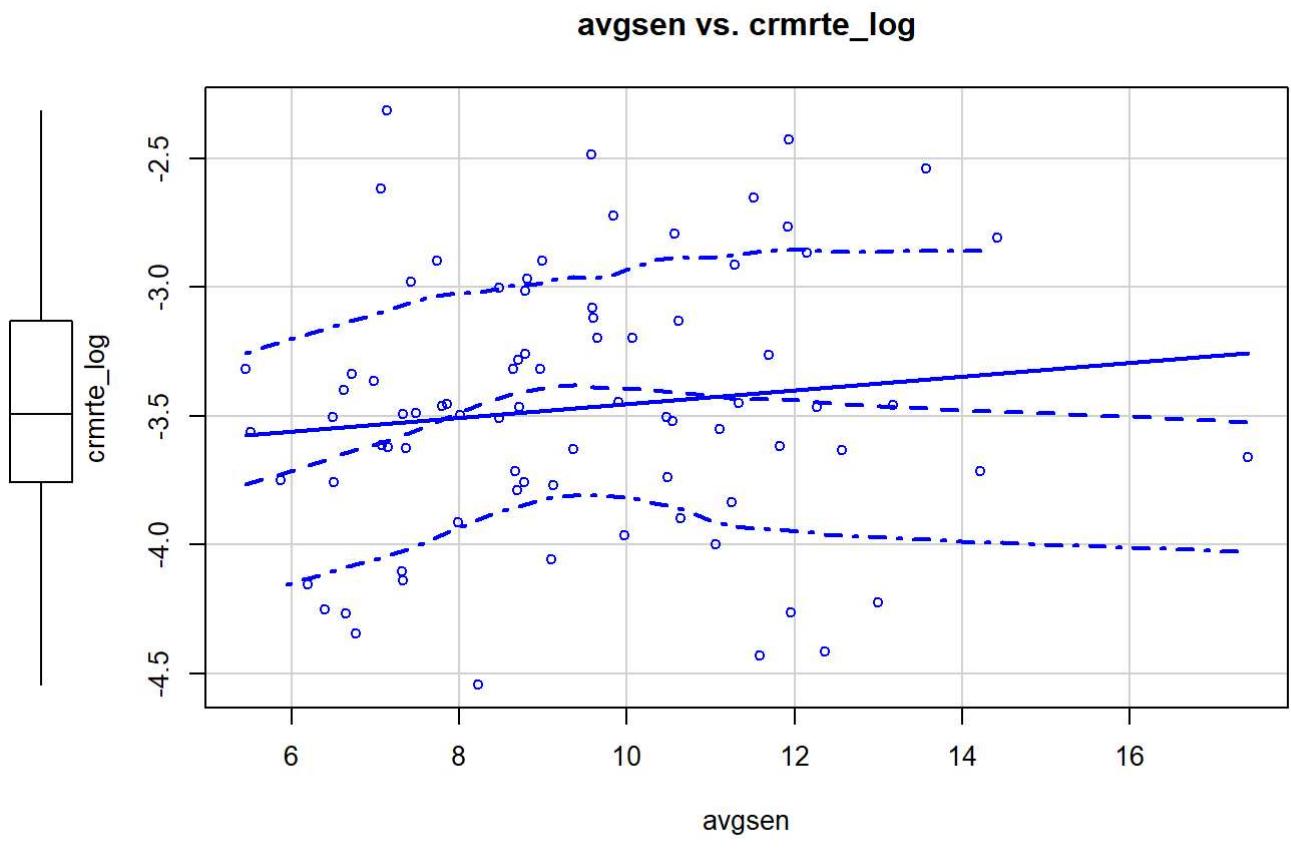


```
scatterplot(data_clean$prbpris,data_clean$crmrte_log, main="prbpris vs. crmrte_log", xlab="prbpris", ylab="crmrte_log")
```

prbpris vs. crmrte_log



```
scatterplot(data_clean$avgsen,data_clean$cmrte_log, main="avgsen vs. crmrte_log", xlab="avgsen",  
 , ylab="cmrte_log")
```



the above scatterplots, we believe that the explanatory variables are displaying relatively linear relationship with dependent variable except for *prbpris*, which seems to be more in parabolic shape. Therefore, we have decided to create a new variable with square of probability of prison to better reveal the linearity.

```
data_clean$prbpris_sq <- data_clean$prbpris^2
```

Fitting model 1:

With the above explained reason, we are building the model1 with the explanatory variable of key interest as below:

$$\text{crmrte_log} = _0 + _1 * \text{prbarr} + _2 * \text{prbconv} + _3 * \text{avgsen} + _4 * \text{prbpris} + u \$$$

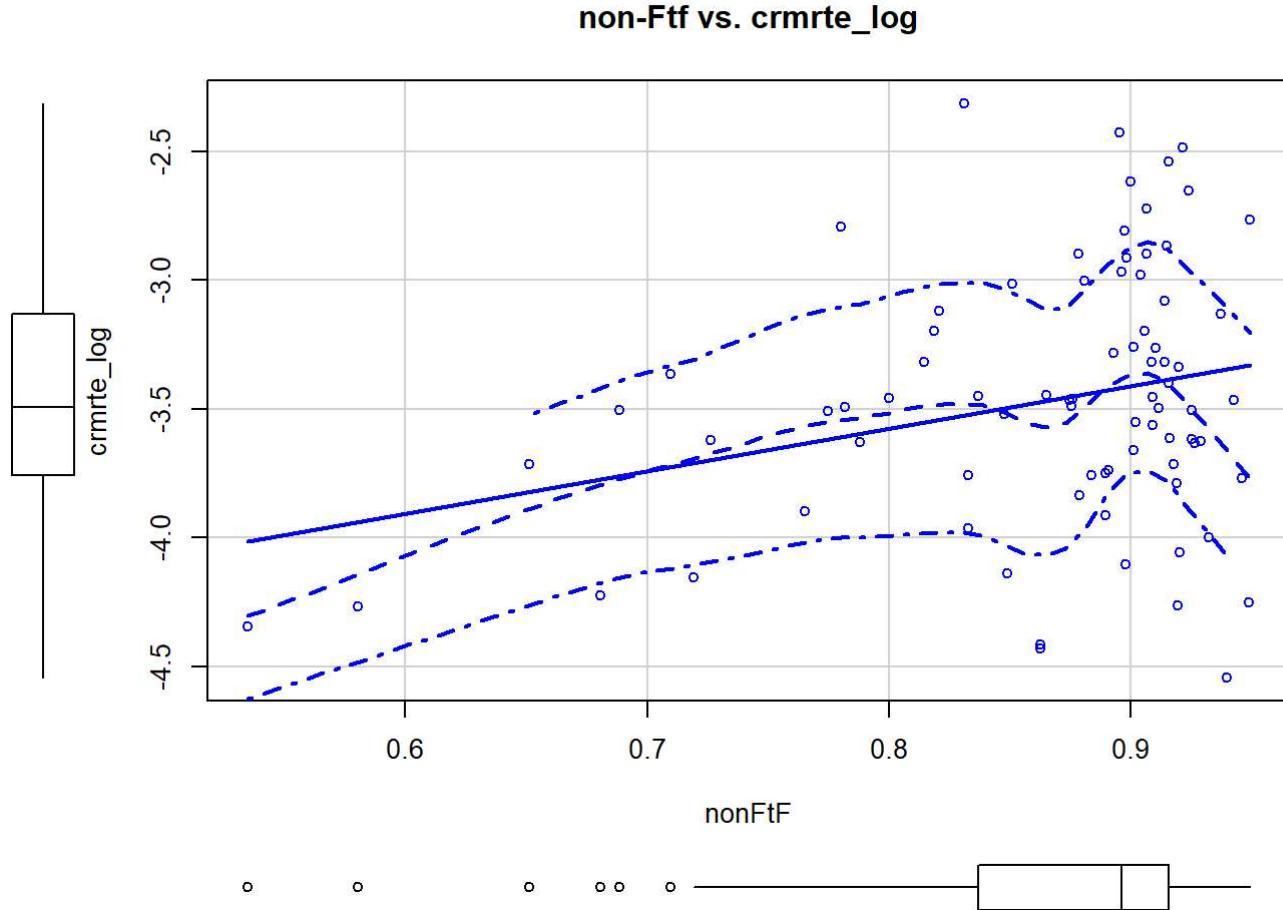
```
model1 <- lm(crmrte_log ~ prbarr + prbconv + avgsen + prbpris, data=data_clean)
model1
```

```
##
## Call:
## lm(formula = crmrte_log ~ prbarr + prbconv + avgsen + prbpris,
##      data = data_clean)
##
## Coefficients:
## (Intercept)      prbarr      prbconv      avgsen      prbpris
## -2.384761     -2.626160     -0.961712      0.009033      0.100288
```

Fitting model 2

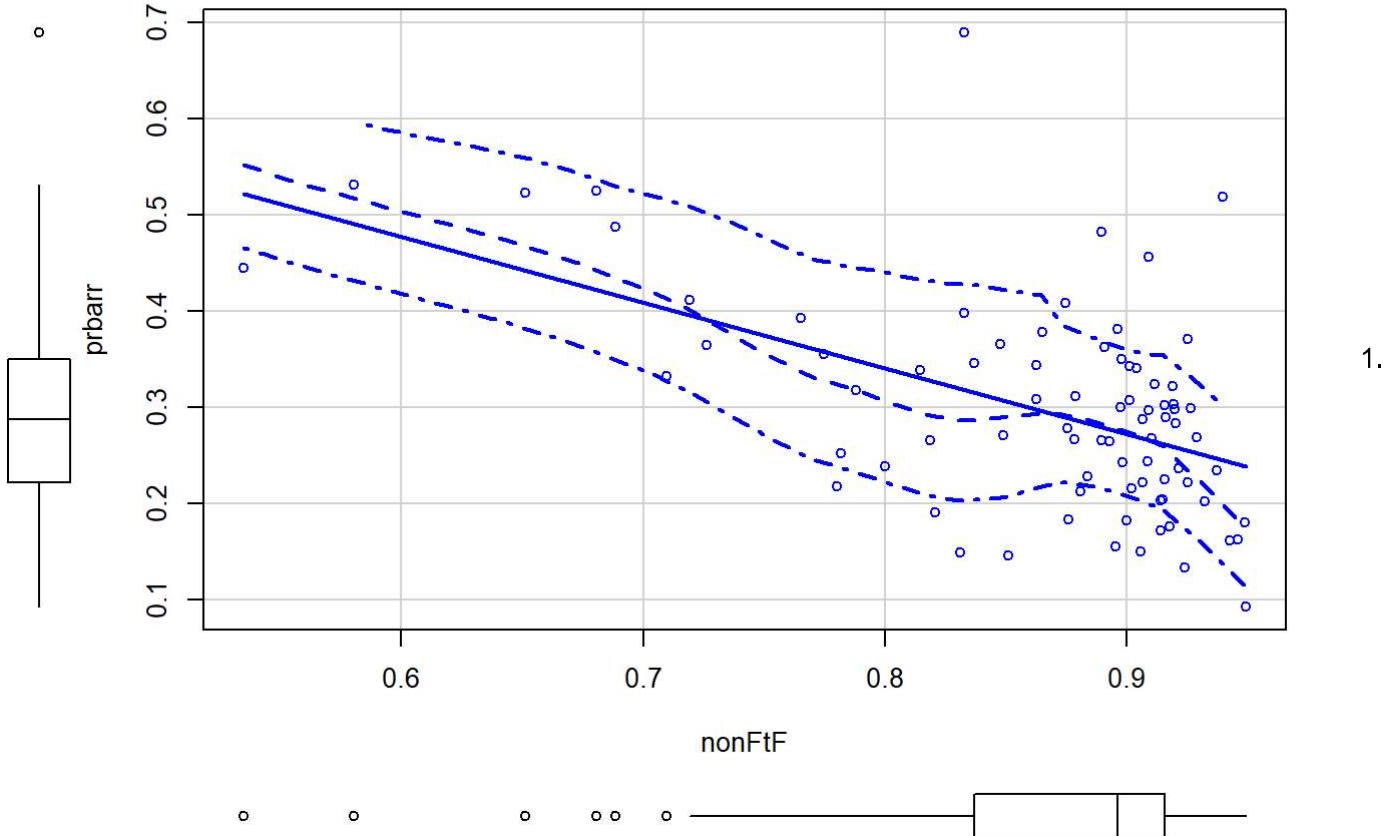
Based on the analysis from research question section, we do believe that the variable *mix* has certain influence on crime rate, especially in *prbarr*. The fact that *prbarr* has strong correlation with *mix* lead us to think that we should really be focusing on the portion of crime that is non face-to-face, which has relatively low *prbarr*. Therefore, we are adding an extra column that reflects percentage of non face-to-face crime:

```
data_clean$nonFtF <- 1-data_clean$mix
scatterplot(data_clean$nonFtF,data_clean$crmrtelog, main="non-Ftf vs. crmrte_log", xlab="nonFtF", ylab="crmrtelog")
```



```
scatterplot(data_clean$nonFtF,data_clean$prbarr, main="non-Ftf vs. prbarr", xlab="nonFtF", ylab="prbarr")
```

non-Ftf vs. prbarr



mix: The above two scatterplot show enough evidence that variable *nonFtF* is an important covariate. Logically, we believe that *nonFtF* should directly impact *prbarr* since the non face-to-face crime tend to be less severe, and there are not as much evidence that can lead to arrest. With the probability of arrest being low for this kind of crime, people are willing to take the risk to commit those crimes. Reducing the non face-to-face crime is very important in reducing the overall *crmrt*. Therefore, we believe that *nonFtF* is crucial in model building and it will help make our model more accurate and less biased.

2. polpc: the magnitude of the *polpc* is at least 100 times smaller than the other probability variables, and we believe that it might add some imbalance in our model building process, therefore we decided to create another variable that is 100 times of polpc:

```
data_clean$polpcMult <- data_clean$polpc*100
```

Fitting model 2:

With the second model, we are building it on top of model 1 but adding more variables that can have influence on the dependent variable *crmrt*. For the purpose of building the model, we added two additional variables: *nonFtF* and *polpcMult*. *nonFtF* is the transformation of mix. It represent the non face to face offense. And *polpcMult* is the transformation of *polpc*. We need to multiply *polpc* by 100 because the numbers are too small. Without the multiplication, *polpc* skewed the model significantly. After the data transformation, the model is as below:

```
crmrt_log = _0 + _1 * prbarr + _2 * prbconv + _3 * avgsen + _4 * prbpris + _5 * nonFtf + _6 * taxpc + _7 * urban
+ _8 * pctymle + _9 * polpcMutl + u $
```

```

data_clean$nonFtf <- (1- data_clean$mix)
data_clean$polpcMult <- data_clean$polpc * 100
model2 <- lm(crmrte_log ~ prbarr + prbconv + avgsen + prbpris_sq + nonFtf + taxpc + urban + pcty
mle + polpcMult, data=data_clean)
model2

```

```

##
## Call:
## lm(formula = crmrte_log ~ prbarr + prbconv + avgsen + prbpris_sq +
##     nonFtf + taxpc + urban + pctymle + polpcMult, data = data_clean)
##
## Coefficients:
## (Intercept)      prbarr      prbconv      avgsen      prbpris_sq
## -4.33062       -1.53728     -0.29128     -0.01616      0.60003
## nonFtf          taxpc        urban      pctymle      polpcMult
## 0.73421        0.00358      0.42856      3.06260      2.62029

```

Based on the model, we notice that nonFtf has a significant positive effect on crmrte_log. That means the higher the non face to face offense ratio, the higher the crmrte_log. This might be interpreted as, non face to face offense tends to be more violent and dangerous than face to face offend, thus get reported more. Taxpc has almost none effect on crmrte. Urban has a relatively significant

Fitting model 3

Bringing in other covariates that we do not believe to be too relevant:

```

model3 <- lm(crmrte_log ~ prbarr+prbconv+prbpris_sq+avgsen+polpcMult+density+taxpc+west+central+
urban+pctmin80+wcon+wtuc+wtrd+wfir+wser+wmfg+wfed+wsta+wloc+nonFtf+pctymle, data=data_clean)
model3

```

```

##
## Call:
## lm(formula = crmrte_log ~ prbarr + prbconv + prbpris_sq + avgsen +
##     polpcMult + density + taxpc + west + central + urban + pctmin80 +
##     wcon + wtuc + wtrd + wfir + wser + wmfg + wfed + wsta + wloc +
##     nonFtf + pctymle, data = data_clean)
##
## Coefficients:
## (Intercept)      prbarr      prbconv      prbpris_sq      avgsen
## -4.5967576     -1.7058163    -0.2850715     0.0050278     -0.0218338
## polpcMult      density      taxpc        west      central
## 2.7118838      0.1146256     0.0032761     -0.1629276     -0.1255685
## urban         pctmin80      wcon        wtuc      wtrd
## -0.0493747     0.0090044     0.0004000     0.0003957     0.0008749
## wfir           wser        wmfg        wfed      wsta
## -0.0023738     -0.0012955    -0.0002377     0.0022246     -0.0017153
## wloc           nonFtf      pctymle
## 0.0019754      0.5863199     3.6248234

```

Here is the latex table in a PDF document:

	<i>Dependent variable:</i>		
	crrmte_log		
	(1)	(2)	(3)
prbarr	-2.626*** (0.423)	-1.537*** (0.465)	-1.706*** (0.305)
prbconv	-0.962*** (0.268)	-0.291 (0.276)	-0.285 (0.182)
avgsen	0.009 (0.020)	-0.016 (0.018)	-0.022* (0.012)
prbpris	0.100 (0.589)		
prbpris_sq		0.600 (0.692)	0.005 (0.454)
nonFtf		0.734 (0.599)	0.586 (0.418)
taxpc		0.004 (0.004)	0.003 (0.003)
west			-0.163 (0.115)
central			-0.126 (0.077)
urban		0.429*** (0.152)	-0.049 (0.163)
pctmin80			0.009*** (0.003)
wcon			0.0004 (0.001)
wtuc			0.0004 (0.0004)
wtrd			0.001 (0.001)
wfir			-0.002*** (0.001)
wser			-0.001 (0.001)
wmfg			-0.0002 (0.0004)
wfed			0.002*** (0.001)
wsta			-0.002** (0.001)
wloc			0.002 (0.001)
pctymle		3.063 (1.868)	3.625*** (1.305)
polpcMult		2.620** (1.030)	2.712*** (0.769)
density			0.115***

Constant	-2.385*** (0.402)	-4.331*** (0.741)	(0.035) -4.597*** (0.568)
Observations	81	81	81
R ²	0.390	0.573	0.870
Adjusted R ²	0.358	0.519	0.820
Residual Std. Error	0.405 (df = 76)	0.351 (df = 71)	0.214 (df = 58)
F Statistic	12.156*** (df = 4; 76)	10.589*** (df = 9; 71)	17.585*** (df = 22; 58)

Note: *p<0.1; p<0.05; p<0.01*

Omitted Variable

1. **education level:** One aspect of education level that is measurable would be the years of education $year_{educ}$.

The years of education could result in the bias over how much impact the percentage of young males $pctymle$ is correlated with $crmrte_{log}$. With the addition of education level, $pctymle$ should really become vague as an explanatory variable. In its place, there should be most likely $pctymle_{lowEduc}$ (percentage of low-education (<6 years) male) that is really more correlated. The bias from this omitted variable should be towards zero.

2. **surveillance camera:** Number of surveillance cameras $surCams$ has some impact on the probability of arrest and the crime rate: Leaving other variables unchanged, we assume that: $\$crmrte_{log} = _0 + _1 * prbarr + _2 * surCams + u \$surCams = _0 + _1 * prbarr + v \$$

Based on our understanding, γ_1 should be positive, and β_2 should be negative. β_1 is negative. Therefore, the OLS coefficient of $prbarr$ will be scaled away to be more negative, gaining statistical significance.

3. **economic growth:** The annual growth in economic $ecoGrowth$ will lead to more job availability and increase in tax income, and will give more funding to the government to hire police forces.

$\$crmrte_{log} = _0 + _1 * taxpc + _2 * ecoGrowth + u \$ SecoGrowth = _0 + _1 * taxpc + v \$$ Based on our understanding, γ_1 should be positive, if β_2 is positive, and β_1 is positive. Therefore, the OLS coefficient of $prbarr$ will be scaled away to be more positive, gaining statistical significance.

4. **arrest rate for minor crimes:** the rate or probability of arrest for minor crimes (vandalism, public drinking, etc.) $prbarr_{minor}$ is the biggest percentage of overall crime rate, and it should be directly related to $prbarr$ and $crmrte_{log}$.

$\$crmrte_{log} = _0 + _1 * prbarr + _2 * prbarr_{minor} + u \$ \$prbarr_{minor} = _0 + _1 * prbarr + v \$$ Based on our understanding, γ_1 should be positive, indicating that actually reducing overall crime rate will usually reduce crime rate for minor crime, and vice versa; β_2 should be negative so OMVB= $_2 < 0$, and β_1 is negative. Therefore, the OLS coefficient of $prbarr$ will be scaled away to be more negative, gaining statistical significance.

5. **average age:** the average age is affecting the crime rate because it is usually the group of people under 30 that commit more crime than people over 30: $\$crmrte_{log} = _0 + _1 * pctymle + _2 * avgAge + u \$ \$avgAge = _0 + _1 * pctymle + v \$$ γ_1 should be negative, and β_2 should be negative so OMVB= $_2 > 0$, and β_1 is positive. Therefore, the OLS coefficient of $pctymle$ will be scaled away to be more positive, gaining statistical significance.

Suggested Statistical Test:

1. Heavier penalties and arrest rate for minor crimes: the analysis suggest that less severe crimes consist of the most crimes committed, and the arrest rate is low for this type of crime. One good test in this regard is to lift the penalties and arrest rate for minor crimes for about 2 weeks, and see if the overall crime rate over those two weeks go down.