Lab 3: Reducing Crime

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Objectives

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1. Introduction and motivation

- Public safety is a major concern for constituents and elected officials alike, especially during elections. By identifying determinants of crime in North Carolina, we can develop policy suggestions to help the campaign deliver on the promise of reducing crime rates, which can in turn bolster their public support. Specifically, we want to understand if crime rates are explained best by geographic, demographic, economic, criminal history variables or a combination of such variables?

2. Help the North Carolina polictical campaign understand the determinants of crime.

- Aim for causal estimates of the determinants of crime & clearly explain how omitted variables may affect conclusions.

3. Generate policy suggestions that are applicable to local government.

- Aim to identify key variables which help local government reducing crime rate in a time- and cost-effective manners.

Variable selection and transformation

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1. What do you want to measure? Make sure you identify variables that will be relevant to the concerns of the political campaign.

- For the response variable, we want to identify the determinants of crime (construct), here expressed with the measured variable $crmrte$. For the explanatory variables, we propose to use variables associated with:
  - geography (e.g. $county$, $west$, and $central$) since crime is often associated with place (see David Weisburd's work) & resultant models could be used to inform policies for specific locales.
  - demographics (e.g. $polpc$, $density$, and $pctymle$) since crime is often associated with demographics & resultant models could be used to help demographics of interest reduce crime.
  - economics (e.g. $wcon$, $wtuc$, and $wtrd$) since wages could conceivably be associated with crime rates & resultant models could be used to justify wage change policies to reduce crime rates.
  - probabilities to be arrested, be convicted, and prison sentence lengths (e.g. $prbarr$, $prbconv$, and $avgsen$) since crimes are often commited by repeat offenders and & resultant models could be used to justify policy changes in prison systems.

2. What covariates help you identify a causal effect? What covariates are problematic, either due to multicollinearity, or because they will absorb some of a causal effect you want to measure?

- We propose to that variables related to geography (e.g. $west$, $central$,etc...), demography (e.g. $density$, $polpc$, etc...), economics (e.g. $taxpc$,fed, etc...), and criminal history (e.g. $prbarr$, $prconv$, etc...) might help us idenifty highly associated, and perhaps $causal$, determinants of crime.
- While there is some mulitcollinearity, for example among the wage variables, it is far from perfect multicollinearity- thus multicollinearity will likely not cause dramtic problems herein.
- The intercepts, β_0, will also be critical to absorb some of the variation from omitted variables that cause crime rates to vary.

3. What transformations should you apply to each variable? This is very important because transformations can reveal linearities in the data, make our results relevant, or help us meet model assumptions.

- The response variable $crmrte$ and all continuous explainatory variables were log-transformed, with natural logs, to reveal a roughly linear relationships with $crmrte$. Categorical variables, such as $west$, $central$, etc... were not log-transformed.
- Additionally, these transformations revealed a roughly linear relationship between mix and $prbarr$ which was be used as justfication to remove the former from the models and simplify future analyses.

4. Are your choices supported by EDA? You will likely start with some general EDA to detect anomalies (missing values, top-coded variables, etc.). From then on, your EDA should be interspersed with your model building. Use visual tools to guide your decisions.

- Yes, the 2D and 3D scatterplot matrices presented below illustrate our choices and transformations of covariates. For example, $crmte$ is related to $density$ but only after log-transformed.

Summary statistics & preliminary sanity checks

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Install and invoke packages

In [2]:
```
# install.packages("car")
# install.packages("GGally")
# install.packages("scatterplot3d")
# install.packages("lmtest")
# install.packages("sandwich")
library(car)
library(stargazer)
library(GGally)
library(scatterplot3d)
library(lmtest)
library(sandwich)
```

Load data

In [3]:
```
df = read.csv("crime_v2.csv",header=T)
```

Check types of variables

In [3]:
```
str(df)
```

```
'data.frame':	97 obs. of  25 variables:
 $ 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 : Factor w/ 92 levels "","`","0.068376102",..: 63 89 13 62 5
2 3 59 78 42 86 ...
 $ 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 ...
```

Perform summary statistics

In [5]:
```
stargazer(df, type="text")
```

```
==================================================================
Statistic N   Mean   St. Dev.   Min    Pctl(25) Pctl(75)    Max
------------------------------------------------------------------
county    91 101.615  58.794   1.000    52.000  152.000   197.000
year      91 87.000   0.000    87.000   87.000   87.000   87.000
crmrte    91  0.033   0.019    0.006    0.021    0.040     0.099
prbarr    91  0.295   0.137    0.093    0.206    0.344     1.091
prbpris   91  0.411   0.080    0.150    0.365    0.457     0.600
avgsen    91  9.647   2.847    5.380    7.340    11.420   20.700
polpc     91  0.002   0.001    0.001    0.001    0.002     0.009
density   91  1.429   1.514   0.00002   0.547    1.568     8.828
taxpc     91 38.055   13.078   25.693   30.662   40.948   119.761
west      91  0.253   0.437    0.000    0.000    0.500     1.000
central   91  0.374   0.486    0.000    0.000    1.000     1.000
urban     91  0.088   0.285    0.000    0.000    0.000     1.000
pctmin80  91 25.495   17.017   1.284    9.845    38.142   64.348
wcon      91 285.358  47.487  193.643 250.782  314.795   436.767
wtuc      91 411.668  77.266  187.617 374.632  443.436   613.226
wtrd      91 211.553  34.216  154.209 190.864  225.126   354.676
wfir      91 322.098  53.890  170.940 286.527  345.354   509.466
wser      91 275.564 206.251  133.043 229.662  280.541  2,177.068
wmfg      91 335.589  87.841  157.410 288.875  359.580   646.850
wfed      91 442.901  59.678  326.100 400.240  478.030   597.950
wsta      91 357.522  43.103  258.330 329.325  382.590   499.590
wloc      91 312.681  28.235  239.170 297.265  329.250   388.090
mix       91  0.129   0.081    0.020    0.081    0.152     0.465
pctymle   91  0.084   0.023    0.062    0.074    0.083     0.249
------------------------------------------------------------------
```

Convert *county*, *west*, *central*, and *urban* from numerics to factors

In [6]:
```
df$county= factor(df$county)
df$west= factor(df$west)
df$central= factor(df$central)
df$urban= factor(df$urban)
```

Convert *prbconv* from factor to numeric

In [7]:
```
df$prbconv = as.numeric(as.character(df$prbconv))
```

```
Warning message in eval(expr, envir, enclos):
“NAs introduced by coercion”
```

Locate missing values, NAs

In [8]:
```
apply(is.na(df), 2, which)
```

county	year	crmrte	prbarr	prbconv	prbpris	avgsen	polpc	density	taxpc	⋯	wtuc	wtrd	v
92	92	92	92	92	92	92	92	92	92	⋯	92	92	
93	93	93	93	93	93	93	93	93	93	⋯	93	93	
94	94	94	94	94	94	94	94	94	94	⋯	94	94	
95	95	95	95	95	95	95	95	95	95	⋯	95	95	
96	96	96	96	96	96	96	96	96	96	⋯	96	96	
97	97	97	97	97	97	97	97	97	97	⋯	97	97	

Note that rows 92-97 are all missing data, NAs

Remove rows with missing values, NAs, for analyses

In [9]:
```
crime.narm <- na.omit(df)
```

Remove the *year* variable - it is a constant

In [10]:
```
df$year = NULL
```

In the *prbarr* & *prbconv* variables, there are instances which are larger than 1.

In [11]:
```
paste("Summary of prbarr variable")
summary(df$prbarr)
paste("Summary of prbconv variable")
summary(df$prbconv)
```

'Summary of prbarr variable'

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
0.09277 0.20568 0.27095 0.29492 0.34438 1.09091       6 
```

'Summary of prbconv variable'

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
0.06838 0.34541 0.45283 0.55128 0.58886 2.12121       6 
```

The prbconv has 10 cases with $p > 1$

In [12]:
```
lenprbconv <- length(df[which(df$prbconv > 1),]$prbconv)
paste("Number of prbconv > 1: ", lenprbconv)
```

'Number of prbconv > 1: 10'

The $prbarr$ has 1 case with p > 1

In [13]:
```
lenprbarr <- length(df[which(df$prbarr > 1),]$prbarr)
paste("Number of prbarr > 1: ", lenprbarr)
```

'Number of prbarr > 1: 1'

Justification for the inclusion of *prbarr* and *prconv* values > 1

As we can see, the two variables described by the study as *prbarr* ('probability' of arrest) and *prbconv* ('probability' of conviction) have values > 1. The first instinct may be to discard the values > 1, since the variable is supposedly a probability and probability *p* can only take valid values $0 \leq p \leq 1$. However, before that, we need to further look into how the study defines the variables. The research by C. Cornwell and W. Trumball (1994), “Estimating the Economic Model of Crime with Panel Data,” Review of Economics and Statistics 76, 360-366. defines

- The probability of arrest (P_a or *prbarr* in the dataset) is the ratio of arrests to offenses
- The probability of conviction (P_c or *prbconv* in the dataset) is the ratio of convictions to arrests

Let's consider the variable *prbconv*. In this case, there are few reasons why the ratio of convictions to arrests may be greater than 1. The police could perhaps make a single arrest of multiple people, which could result in multiple convictions. Or a single person could be arrested but convicted for multiple crimes (e.g. a single arrest could lead to someone being convicted of assualt with a deadly weapon, breaking+entering and theft). Therefore, we do not consider *prbconv* to strictly indicate probability (which would be constrained by $0 \leq p \leq 1$). Moreover, instead of truncating entries > 1 to 1 or discarding the values completely, we will leave the entries in the dataset used for the analysis. We have used the same approach for *prbarr* and again did not discard values > 1. The consequences of the inclusion of the *prbarr* and *prconv* values > 1 will be reflected in our interpretation of the coefficients below.

More formally, in probability theory, all variables should follow $f(x) \in [0, 1]$ for all $x \in \Omega$. However, the $prbarr$ and $prbconv$ indicated the ratio of arrests to offenses and the ratio to conviction, respectively. These two variables, and all observations therein (not just those >1) do not satisfy the axioms of probability theory. Therefore, the $prbarr > 1$ and $prbconv > 1$ were kept for OLS analysis but are not interpreted probabilistically below.

The dimensions of the final dataframe

In [14]:
```
dim(crime.narm)
```

91 25

Exploratory data analyses

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Check the scale among variables

In [15]:
```
head(crime.narm)
```

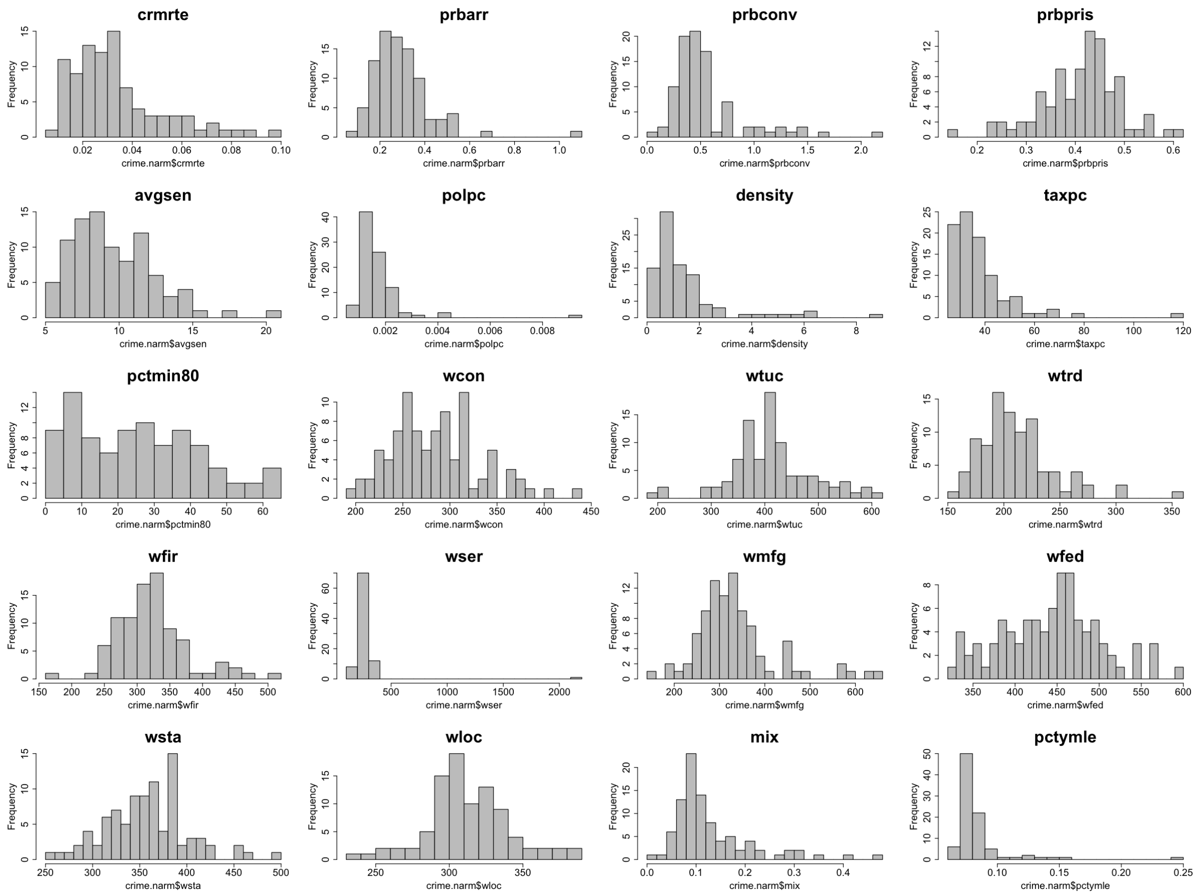
county	year	crmrte	prbarr	prbconv	prbpris	avgsen	polpc	density	taxpc
1	87	0.0356036	0.298270	0.5275960	0.436170	6.71	0.00182786	2.4226327	30.99368
3	87	0.0152532	0.132029	1.4814800	0.450000	6.35	0.00074588	1.0463320	26.89208
5	87	0.0129603	0.444444	0.2678570	0.600000	6.76	0.00123431	0.4127659	34.81605
7	87	0.0267532	0.364760	0.5254240	0.435484	7.14	0.00152994	0.4915572	42.94759
9	87	0.0106232	0.518219	0.4765630	0.442623	8.22	0.00086018	0.5469484	28.05474
11	87	0.0146067	0.524664	0.0683761	0.500000	13.00	0.00288203	0.6113361	35.22974

Figure 1: Distributions of variables

- Note that most variables are not normally distributed

In [16]:

```
options(repr.plot.height = 15, repr.plot.width = 20, repr.plot.pointsize
= 10)
par(mfrow = c(5,4))
par(mar=c(6,5,4,2))
hist(crime.narm$crmrte,breaks=20, main = "crmrte",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$prbarr,breaks=20, main = "prbarr",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$prbconv,breaks=20, main = "prbconv",cex.lab=1.5,cex.main
=2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$prbpris,breaks=20, main = "prbpris",cex.lab=1.5,cex.main
=2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$avgsen,breaks=20, main = "avgsen",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$polpc,breaks=20, main = "polpc",cex.lab=1.5,cex.main=2.5
,cex.axis=1.5,col="grey78")
hist(crime.narm$density,breaks=20, main = "density",cex.lab=1.5,cex.main
=2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$taxpc,breaks=20, main = "taxpc",cex.lab=1.5,cex.main=2.5
,cex.axis=1.5,col="grey78")
hist(crime.narm$pctmin80,breaks=20, main = "pctmin80",cex.lab=1.5,cex.ma
in=2.5,cex.axis=1.5,col="grey78")
hist(crime.narm$wcon,breaks=20, main = "wcon",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wtuc,breaks=20, main = "wtuc",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wtrd,breaks=20, main = "wtrd",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wfir,breaks=20, main = "wfir",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wser,breaks=20, main = "wser",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wmfg,breaks=20, main = "wmfg",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wfed,breaks=20, main = "wfed",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wsta,breaks=20, main = "wsta",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$wloc,breaks=20, main = "wloc",cex.lab=1.5,cex.main=2.5,c
ex.axis=1.5,col="grey78")
hist(crime.narm$mix,breaks=20, main = "mix",cex.lab=1.5,cex.main=2.5,ce
x.axis=1.5,col="grey78")
hist(crime.narm$pctymle,breaks=20, main = "pctymle",cex.lab=1.5,cex.main
=2.5,cex.axis=1.5,col="grey78")
```

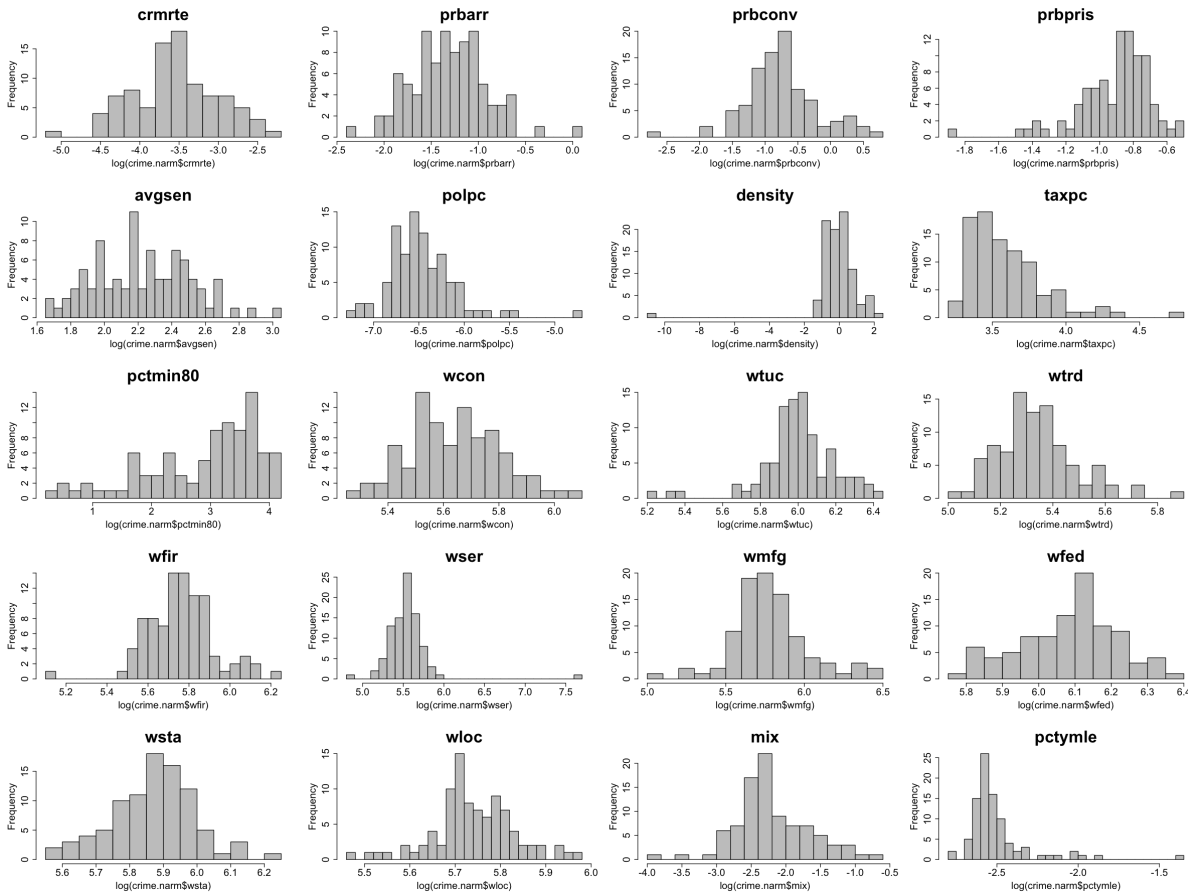


> All the analyses were based on the log-transformed data because most variables show positive skew (except: *prbpris, wtuc, wfir, and wloc*) and the scale differences among variables are incompatible and range from 0.005 to 2177.1.

Figure 2: Distributions of variables after log-transformation

- Note that log-transformation resolved most instances of non-symetric distributions

In [17]:
```
options(repr.plot.height = 15, repr.plot.width = 20, repr.plot.pointsize
= 10)
par(mfrow = c(5,4))
par(mar=c(6,5,4,2))
hist(log(crime.narm$crmrte),breaks=20, main = "crmrte",cex.lab=1.5,cex.m
ain=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$prbarr),breaks=20, main = "prbarr",cex.lab=1.5,cex.m
ain=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$prbconv),breaks=20, main = "prbconv",cex.lab=1.5,ce
x.main=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$prbpris),breaks=20, main = "prbpris",cex.lab=1.5,ce
x.main=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$avgsen),breaks=20, main = "avgsen",cex.lab=1.5,cex.m
ain=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$polpc),breaks=20, main = "polpc",cex.lab=1.5,cex.mai
n=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$density),breaks=20, main = "density",cex.lab=1.5,ce
x.main=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$taxpc),breaks=20, main = "taxpc",cex.lab=1.5,cex.mai
n=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$pctmin80),breaks=20, main = "pctmin80",cex.lab=1.5,c
ex.main=2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wcon),breaks=20, main = "wcon",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wtuc),breaks=20, main = "wtuc",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wtrd),breaks=20, main = "wtrd",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wfir),breaks=20, main = "wfir",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wser),breaks=20, main = "wser",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wmfg),breaks=20, main = "wmfg",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wfed),breaks=20, main = "wfed",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wsta),breaks=20, main = "wsta",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$wloc),breaks=20, main = "wloc",cex.lab=1.5,cex.main=
2.5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$mix),breaks=20, main = "mix",cex.lab=1.5,cex.main=2.
5,cex.axis=1.5,col="grey78")
hist(log(crime.narm$pctymle),breaks=20, main = "pctymle",cex.lab=1.5,ce
x.main=2.5,cex.axis=1.5,col="grey78")
```



Check correlations between dependent variable (*crmrte*) and independent variables

Figure 3: Crime and geography

- Note that (i) there is no perfect collinearity between the explanatory variables (ii) log(*density*) is clearly related to log(*crmrte*).

In [18]:
```
options(repr.plot.height = 15, repr.plot.width = 20, repr.plot.pointsize
= 10)
pairs(~log(crmrte)
      + log(density)
      + jitter(as.numeric(west),0.5)
      + jitter(as.numeric(central),0.5)
      + jitter(as.numeric(urban),0.5),
      data = crime.narm,
      cex.labels=3, lower.panel = NULL,
      upper.panel=panel.smooth,
      pch=1,cex=3,lwd=3,col="grey55")
```

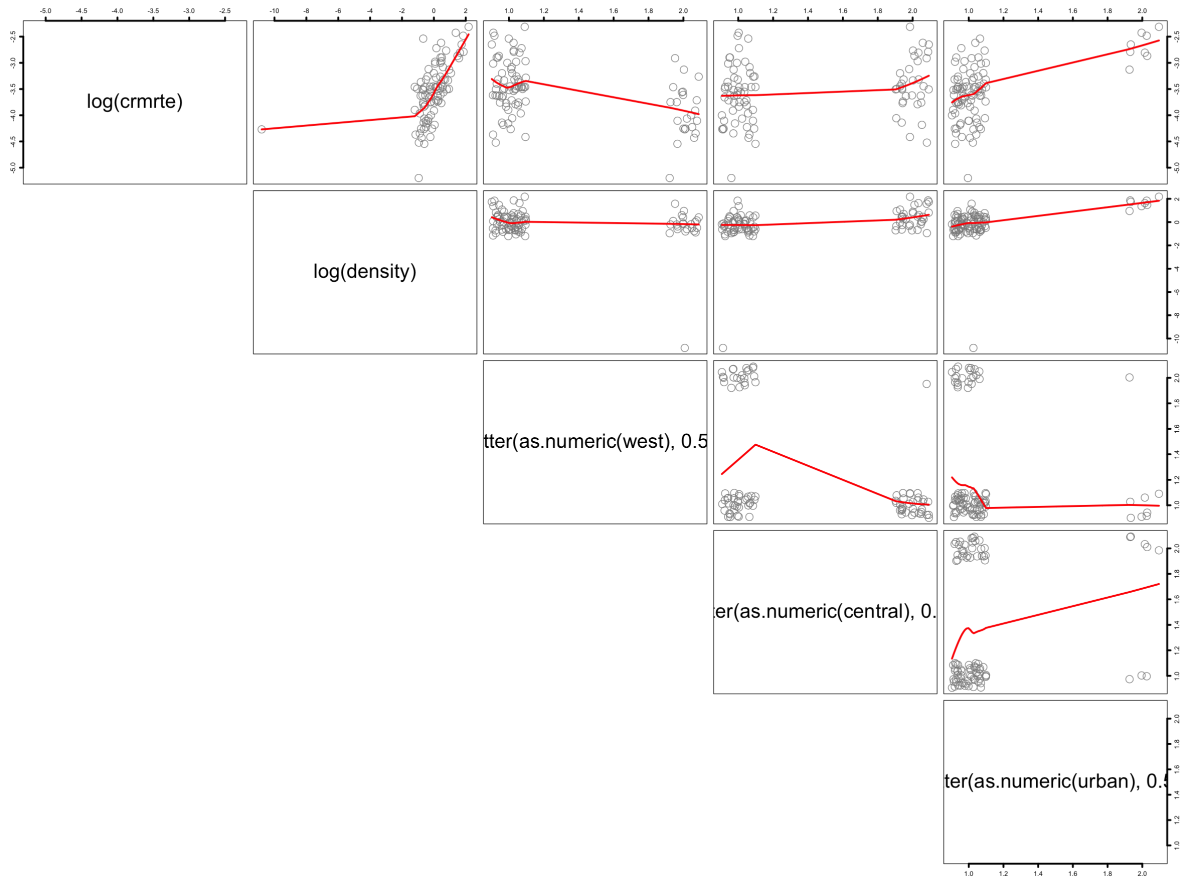


Figure 4: Crime and demographics

- Note that (i) there is no perfect collinearity between the explanatory variables (ii) log(*polpc*) is clearly related to log(*crmrte*).

In [19]:
```
options(repr.plot.height = 15, repr.plot.width = 20, repr.plot.pointsize
= 10)
pairs(~log(crmrte)
      + log(polpc)
      + log(density)
      + log(pctmin80)
      + log(pctymle),
      data = crime.narm,
      cex.labels=3, lower.panel = NULL,
      upper.panel=panel.smooth,
      pch=1,cex=3,lwd=3,col="grey55")
```

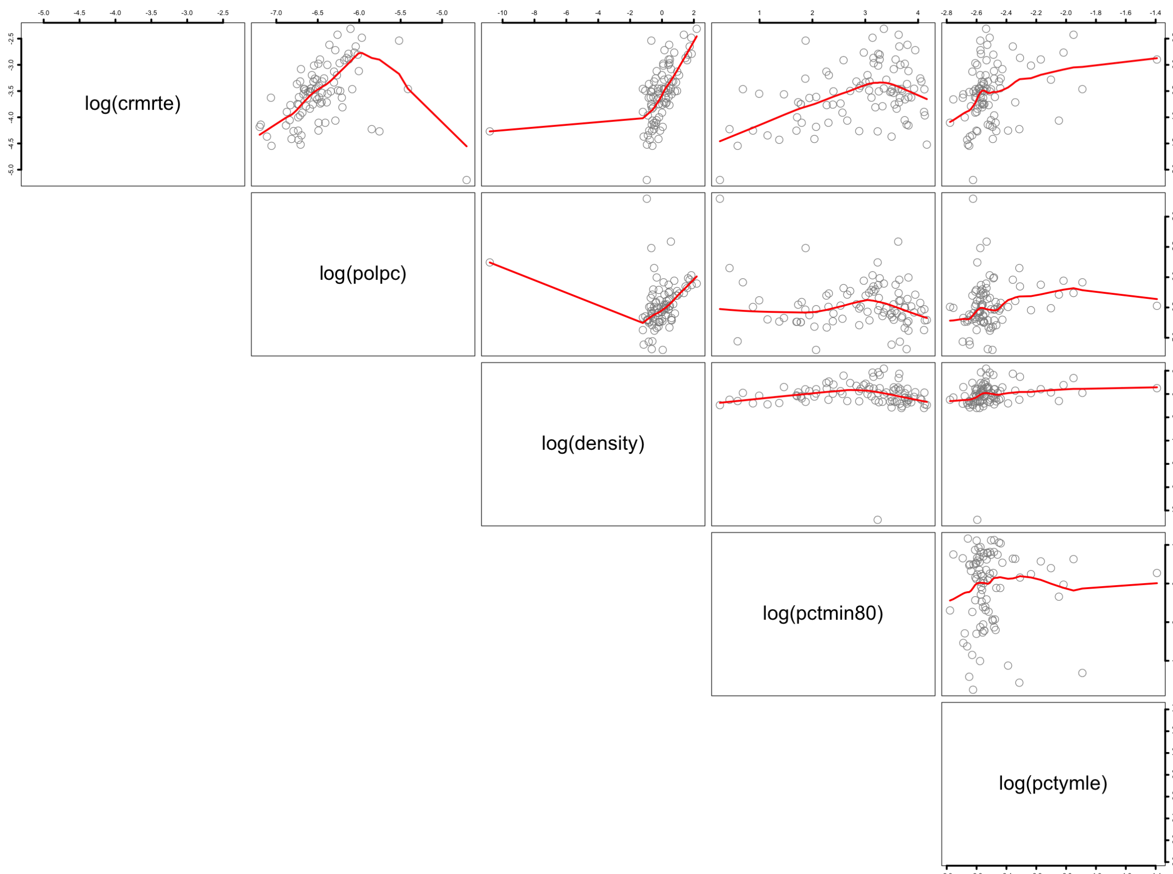


Figure 5: Crime and economics

- Note that (i) there is no perfect collinearity between the explanatory variables (ii) log(*wfed*), log(*wcon*), and log(*wmfg*) are clearly related to log(*crmrte*).

In [20]:
```
options(repr.plot.height = 20, repr.plot.width = 20, repr.plot.pointsize
= 10)
pairs(~log(crmrte)
      + log(taxpc)
      + log(wcon)
      + log(wtuc)
      + log(wtrd)
      + log(wfir)
      + log(wser)
      + log(wmfg)
      + log(wfed)
      + log(wsta)
      + log(wloc),
      data = crime.narm,
      cex.labels=2.5, lower.panel = NULL,
      upper.panel=panel.smooth,
      pch=1,cex=0.8,lwd=2,col="grey55")
```

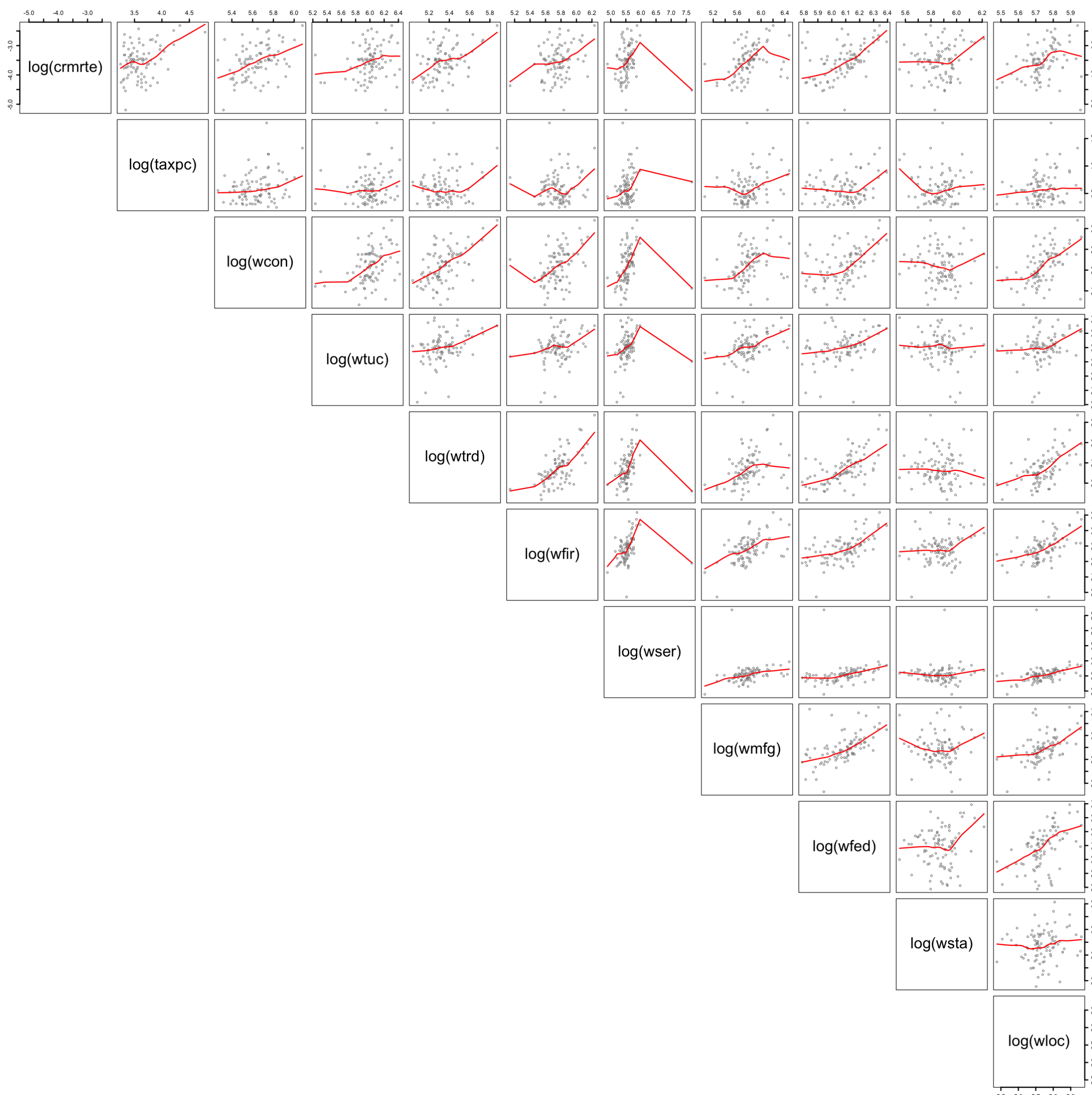
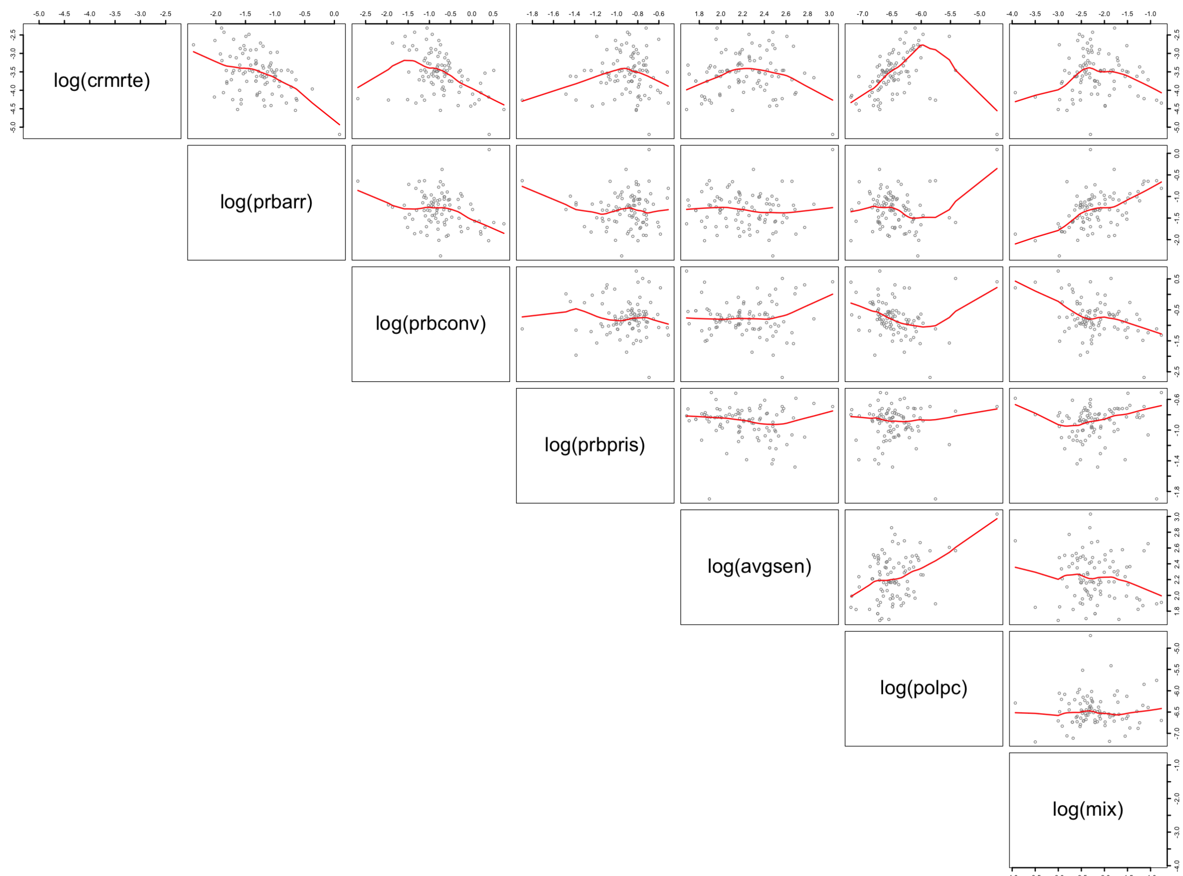


Figure 6: Crime and propensity to commit crime, be arrested, and sentence lengths

- Note that (i) there is no perfect collinearity between the explanatory variables (ii) log(*prbarr*) and log(*prconv*) are clearly related to log(*crmrte*).

In [21]:
```
options(repr.plot.height = 15, repr.plot.width = 20, repr.plot.pointsize
= 10)
pairs(~log(crmrte)
      + log(prbarr)
      + log(prbconv)
      + log(prbpris)
      + log(avgsen)
      + log(polpc)
      + log(mix),
      data = crime.narm,
      cex.labels=3, lower.panel = NULL,
      upper.panel=panel.smooth,
      pch=1,cex=1,lwd=2,col="grey55")
```



Inferential analysis

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A OLS model with all variables A OLS model with all variables

$$\ln(crmrte) = \beta_0 + \beta_1 \ln(density) + \beta_2 \ln(polpc) + \beta_3 \ln(wfed) + \beta_4 \ln(wcon) + \beta_5 \ln(wtuc) + \beta_6 \ln(wtr$$
$$+ \beta_{10} \ln(wsta) + \beta_{11} \ln(wloc) + \beta_{12} \ln(prbarr) + \beta_{13} \ln(prbconv) + \beta_{14} \ln(prbpris) + \beta_{15} \ln(avgsen) +$$
$$(pctmin80) + \beta_{20} \ln(pctymle) + u$$

In [34]:
```
# build OLS model with all variables
m_all <- lm(log(crmrte) ~ log(density) + log(polpc) + log(wfed) + log(wc
on) +
                          log(wtuc) + log(wtrd) + log(wfir) + log(wser)
+
                          log(wmfg) + log(wsta) + log(wloc) +
                          log(prbarr) + log(prbconv) + log(prbpris) + lo
g(avgsen) +
                          factor(west) + factor(urban) + factor(central)
+ log(pctmin80) + log(pctymle),
                          data = crime.narm)
```

Robust standard errors

In [35]:
```
# Compute robust standard errors
se.m_all = sqrt(diag(vcovHC(m_all)))
```

Assess percent of variation if *crmrte* that is explained by all explanatory variables

In [36]:
```
# check adjusted r squared
paste("adj.r.squared: ", summary(m_all)$adj.r.squared)
```

'adj.r.squared: 0.790953213256509'

> The accuracy of prediction would be high by incorporating all variables. The OLS model with all variables shows adjusted $R^2 = 0.791$. The risk of model overfitting and the cost (e.g. computing power, data collection, etc) would be increased at the same time. Therefore, the variables were sorted in different categories based on their characteristics.

For inferential analysis, we would like to achieve 3 goals

1. Models that includes the covariates of each category to examine the robustness and accuracy of models.
2. The model that includes key explanatory variables and only covariates that you believe increase the accuracy of your results without introducing substantial bias. This model should strike a balance between accuracy and parsimony and reflect your best understanding of the determinants of crime.
3. The model with only the explanatory variables of key interest and no other covariates.

1. Models that were built based on each category

Population, goverment income

In [37]:
```
mp4 <- lm(log(crmrte) ~ log(density) + log(polpc) + log(taxpc), data = c
rime.narm)
paste("adj.r.squared: ", summary(mp4)$adj.r.squared)
```

'adj.r.squared: 0.336758991135941'

Employee Income

In [38]:
```
me10 <- lm(log(crmrte) ~ log(wcon) + log(wtuc) + log(wtrd) +
          log(wfir) + log(wser) + log(wmfg) + log(wfed) +
          log(wsta) + log(wloc), data = crime.narm)
paste("adj.r.squared: ", summary(me10)$adj.r.squared)
```

'adj.r.squared: 0.25532421106584'

Minority and young male

In [39]:
```
mm3 <- lm(log(crmrte) ~ pctmin80 + pctymle, data = crime.narm)
paste("adj.r.squared: ", summary(mm3)$adj.r.squared)
```

'adj.r.squared: 0.115886674982097'

Geographic factors

In [40]:
```
mg4 <- lm(log(crmrte) ~ factor(west) + factor(central) + factor(urban),
data = crime.narm)
paste("adj.r.squared: ", summary(mg4)$adj.r.squared)
```

'adj.r.squared: 0.35999306318057'

Crime outcomes

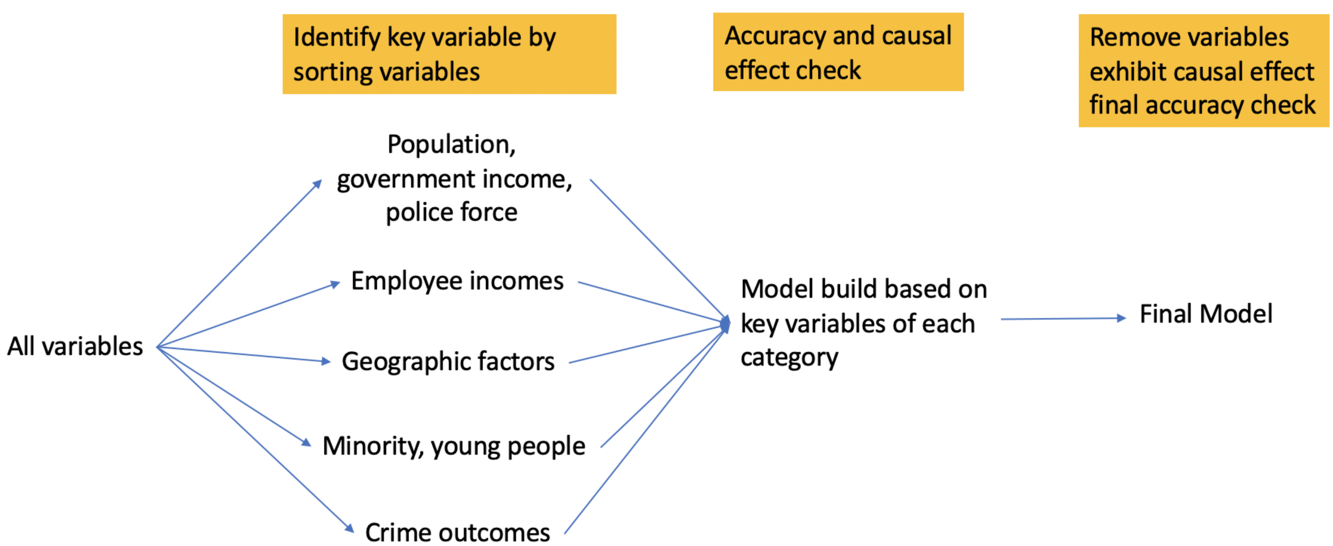
In [41]:
```
mc6 <- lm(log(crmrte) ~ log(prbarr) + log(prbconv) +
          log(prbpris) + log(avgsen) + log(mix), data = crime.narm)
paste("adj.r.squared: ", summary(mc6)$adj.r.squared)
```

'adj.r.squared: 0.397593490939127'

> The OLS models based on the categories do not provide competitive explanations of the variation in *crmrte*. The OLS model of population and goverment income varibales shows adjusted $R^2 = 0.337$. The OLS model of minority and young male varibales shows adjusted $R^2 = 0.116$. The OLS model of geographic factors varibales shows adjusted $R^2 = 0.360$. The OLS model of crime outcomes varibales shows adjusted $R^2 = 0.398$. Therefore, identification of key variables from each category were applied to build the new OLS model.

2. The model that includes key explanatory variables.

The procedure of explanatory key variables of interest



> Here, we first applied bivariate OLS model ($\ln(crmrte) = \beta_0 + \beta_1 \ln(X_1)$) to identify the independent variables that significantly affect crime rate. Of the 24 candidate explanatory variables, a total of 12 variables (*taxpc* from government income; *wcon, wtrd, wfir, wmfg, wloc*, and *wfed* from employee incomes; *west* and *urban* from geographic factors; *pctmin80* from minority; *prbarr* and *prbconv* from crime outcomes) were identified from each category as showed above. The details of analysis is showed in the "Appendix" section.

The model with the explanatory variables of interest

$$\ln(crmrte) = \beta_0 + \beta_1 \ln(taxpc) + \beta_2 \ln(wcon) + \beta_3 \ln(wtrd) + \beta_4 \ln(wfir) + \beta_5 \ln(wmfg) + \beta_6 \ln(wloc) + \beta_{10} \ln(pctmin80) + \beta_{11} \ln(prbarr) + \beta_{12} \ln(prbconv) + u$$

In [42]:
```
# build OLS model with associated variables
m_associated <- lm(log(crmrte) ~ log(taxpc) + log(wcon) + log(wtrd) + lo
g(wfir) +
                          log(wmfg) + log(wloc) + log(wfed) +
                          factor(west) + factor(urban) + log(pctmin80) +
                          log(prbarr) + log(prbconv),
                          data = crime.narm)
paste("adj.r.squared: ", summary(m_associated)$adj.r.squared)
```

'adj.r.squared: 0.700162294107207'

The model with only the variables of key interest

$$\ln(crmrte) = \beta_0 + \beta_1 \ln(prbarr) + \beta_2 \ln(prbconv) + \beta_3 \ln(wfed) + \beta_4 \ln(pctmin80) + \beta_5 \ln(prbarr) \cdot (p$$

In [51]:
```
# build OLS model with key variables
m_key =(lm(log(crmrte) ~ log(prbarr) + log(prbconv) +
                          log(wfed) + log(pctmin80) +
                          log(prbarr)*log(prbconv),
                          data = crime.narm))
paste("adj.r.squared: ", summary(m_key)$adj.r.squared)
```

'adj.r.squared: 0.72555676634597'

Regression table

In [52]:
```
# Compute robust standard errors
se.m_associated = sqrt(diag(vcovHC(m_associated)))
se.m_key = sqrt(diag(vcovHC(m_key)))
# We pass the standard errors into stargazer through the se argument.
stargazer(m_all, m_associated, m_key,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.m_all, se.m_associated, se.m_key),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

	Dependent variable:		
	log(crmrte)		
	(1)	(2)	(3)
log(density)	0.128		
	(0.178)		
log(polpc)	0.499*		
	(0.225)		
log(taxpc)		0.115	
		(0.333)	
log(wfed)	0.563	1.037*	1.356***
	(0.554)	(0.500)	(0.385)
log(wcon)	0.257	0.152	
	(0.262)	(0.237)	
log(wtuc)	0.109		
	(0.355)		
log(wtrd)	0.360	0.090	
	(0.341)	(0.361)	
log(wfir)	-0.291	-0.199	
	(0.425)	(0.422)	
log(wser)	-0.323		
	(0.177)		
log(wmfg)	0.022	0.266	
	(0.214)	(0.209)	
log(wsta)	-0.046		
	(0.363)		
log(wloc)	0.038	0.301	
	(0.702)	(0.561)	
log(prbarr)	-0.513***	-0.536***	-0.384**
	(0.154)	(0.089)	(0.120)
log(prbconv)	-0.332*	-0.453***	-0.021
	(0.138)	(0.096)	(0.190)
log(prbpris)	-0.284		
	(0.235)		
log(avgsen)	-0.346		
	(0.177)		
factor(west)1	0.049	-0.007	
	(0.164)	(0.115)	

factor(urban)1	0.083	0.136	
	(0.221)	(0.189)	
factor(central)1	-0.087		
	(0.110)		
log(pctmin80)	0.263***	0.206**	0.215***
	(0.070)	(0.071)	(0.032)
log(pctymle)	0.109		
	(0.304)		
log(prbarr):log(prbconv)			0.372*
			(0.147)
Constant	-5.244	-15.373***	-13.286***
	(4.416)	(3.038)	(2.318)
Observations	91	91	91
Adjusted R2	0.791	0.700	0.726
Note:	*p<0.05;	**p<0.01;	***p<0.001

Interpretation of coefficients

m_all:

The m_all model includes all 20 independent variables available in the dataset. Since both the dependent and explanatory variables are log transformed, we can describe the impact of a log-tranformed explanatory variable β_i such a A% change in β_i (holding all other variables constant) results in an B% change in crime rate.

- β_1: For every 1% in increase in density, the crime rate increases by 0.128% or to put things in perspective, a 10% increase in population would only result in a 1.2% increase in crime rate which is practically insignificant. This is also statistically insifigicant ($p > 0.05$) and we fail to reject the null hypothesis that the slope is 0 i.e. H_0: $\beta_1 = 0$.
- β_2: For every 1% in increase in police per capita, the crime rate increases by 0.5%. This is counter intuitive but can be indicative of the fact that when crime increases, more police resources per capita may be deployed and not that more police per capita causes a higher crime rate. The null hypothesis that H_0: $\beta_2 = 0$ can be rejected, though it should be noted that the associated p value only satisfies ($p < 0.05$)
- *Wage coefficients* β_3 - β_{11} : We see here that when all types of wages are included, any 10% increase in $wfed$, $wcon$, $wtuc$,$wtrd$,$wmfg$ or $wloc$ result in no more than a 6% increase increase in crime rate, with the impact of federal wage being the highest at 5.6% and manufacturing wages having the lowest impact at 0.2% increase in crime rate. In many cases, the impact to crime rate is practically neglible, e.g in the case of manufacturing wages. On the other hand, any 10% increase in $wfir$, $wser$ or $wsta$ is associated with upto a 3.2% decrease in crime rate but again the impact is practically insignificant. Moreover, all the coefficients β_3 - β_{11} are statistically insignificant (each associated p , $p > 0.05$) and we fail to reject the null hypothesis for each of these variables H_0: $\beta_i = 0$ for i = 3, 4, ... 11
- β_{12} : For every 10% increase in the 'probability' of arrest, we see that crime rate reduces by 5.3%. This coefficient is statiscally significant and thus reject the null hypothesis H_0: $\beta_{12} = 0$ since the associated p value $p < 0.001$. This decrease is also practically significant since their is the potential to impact the crime in an area in an actionable and positive manner. One reason for this negative relation between the independent and explanatory variable may be that once a person is arrested, their opportunity to commit crime is reduced.
- β_{13} : For every 10% increase in the 'probability' (or rather propensity) of convictions, there is 3.3% decrease in crime rate. This coefficient is statiscally significant and thus reject the null hypothesis H_0: $\beta_{12} = 0$ since the associated p value $p < 0.05$. This impact of this coefficient may be of small but important practically significant in that perhaps people are less likely to commit a crime if they face the prospect of conviction.
- β_{14} : For every 10% increase in the 'probability' of a prison sentence, there is 2.8% decrease in crime rate. While this coefficient may of limited practical significance in that prospect of prison time may lead to few crimes being the commited, in this model, this coefficient is statiscally insignificant ($p > 0.05$).
- β_{15} : For every 10% increase in the length of prison sentence, there appears to be a 3.5% decrease in crime rate. While this coefficient may be of practical significance in that perhaps longer the a prison sentences provide less opportunities to commit crime or even that the experience of prison deters recidivism, in this model β_{15} coefficient is statiscally insignificant ($p > 0.05$).

m_associated:

- From bivariate OLS models of each category, we identified the regressors that rejected null hypothesis H_0: $\beta_1 = 0$ ($p < 0.05$). The coefficients of these regressors are significantly affecting crime rate. However, when we put these variables into one multivariable OLS model, the effects of *taxpc*, *wcon*, *wtrd*, *wfir*, *wmfg*, *wloc*, *west*, and *urban* on crime rate become statistically and practically insignificant ($p > 0.05$).

- For each unit increase in the log-transformed weekly wages of federal employees (*log(wfed)*), log-transformed crime rate increases 1.03 units. This coefficient is statistically and practically significant. The p-value associated with $H_0\colon \beta_7 = 0$ is $p < 0.05$- the slope is different from 0. When converted back to the original units, this coefficient represents a 2.8 unit increase in crime rates (crimes committed/person) for every unit increase in weekly wages for federal employees.
- For each unit increase in the log-transformed percent minority (*log(pctmin80)*), the log-transformed crime rate increases by 0.206. This coefficient is a statistically and practically significant explanatory variable. The p-value associated with $H_0\colon \beta_10 = 0$ is $p < 0.01$- the slope is different from 0. From a practical perspective, this coefficient seems to represent an important driver of crime rates/person.
- For each unit increase in the log-transformed 'probability' or propensity to be arrested (*log(prbarr)*), the log-transformed crime rate decreases by -0.536 units. This coefficient is statistically and practically significant. The p-value associated with $H_0\colon \beta_{11} = 0$ is $p < 0.001$- the slope is different from 0. From a practical perspective, this coefficient represents a small but perhaps important decrease in crime rates/person. Perhaps people are less likely to commit a crime if they are more likely to be arrested.
- For each unit increase in the log-transformed 'probability' or propensity to be arrested (*log(prbconv)*), the log-transformed crime rate decreases by -0.453 units. This coefficient is statistically and practically significant. The p-value associated with $H_0\colon \beta_{12} = 0$ is $p < 0.001$- the slope is different from 0. From a practical perspective, this coefficient represents a small but perhaps important decrease in crime rates/person. Perhaps people are less likely to commit a crime if they are more likely to be serving a sentence in prison. .
- Finally, the intercept, β_0, is significant and negative, -15. This large and statistically significant coefficient may provide evidence that we have omitted many variables and the intercept is absorbing the variation of those variables.

m_key:

- For each unit increase in the log-transformed weekly wages of federal employees (*log(wfed)*), log-transformed crime rate increases 1.3 units. This coefficient is statistically and practically significant. The p-value associated with $H_0\colon \beta_3 = 0$ is $p < 0.001$- the slope is different from 0. When converted back to the original units, this coefficient represents a 3.6 unit increase in crime rates (crimes committed/person) for every unit increase in weekly wages for federal employees.
- For each unit increase in the log-transformed 'probability' or propensity to be arrested (*log(prbarr)*), the log-transformed crime rate decreases by -0.384. Despite the failure of *prbarr* to satisfy the axioms of probability theory, it still constitutes and statistically and practically significant explanatory variable. The p-value associated with $H_0\colon \beta_1 = 0$ is $p < 0.01$- the slope is different from 0. From a practical perspective, this coefficient represents a small but perhaps important decrease in crime rates/person. Perhaps people are less likely to commit a crime if they are more likely to be arrested.
- For each unit increase in the log-transformed percent minority (*log(pctmin80)*), the log-transformed crime rate increases by 0.215. This coefficient is a statistically and practically significant explanatory variable. The p-value associated with $H_0\colon \beta_4 = 0$ is $p < 0.001$- the slope is different from 0. From a practical perspective, this coefficient seems to represent an important driver of crime rates/person. When converted back to the original units, it looks like every unit increase in *pctmin80* corresponds to 1.2 unit increase in the number of crimes committed/person.
- There is an interaction between *log(prbarr)* and *log(prbconv)*. The log-transformed crime rate depends on the relationship between *log(prbarr)* and *log(prbconv)*. In other words, the effect of *log(prbconv)* on *log(crmrte)* depends on the values of *log(prbarr)*. This interaction is positive- the difference between the *log(prbarr)* and *log(prbconv)* slopes is positive. This interaction is statistically and of weak practical significance. The p-value associated with $H_0\colon \beta_1 = \beta_2 = 0$ is $p < 0.05$- the slopes are different from 0.

Although the effect of *log(prbconv)* on *log(crmrte)* depends on the values of *log(prbarr)*, the slopes of the *log(prbarr)* and *log(prbconv)* are only midly positive.

- Finally, the intercept, β_0, is significant and negative, -13. This large and statisically significant coefficient

Regression diagnostics

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Figure 7: Diagnostic plots for model with all explanatory variables

In [34]:
```
options(repr.plot.height = 3, repr.plot.width = 8, repr.plot.pointsize =
10)
par(mfrow = c(1,4))
plot(m_all, which=1, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_all, which=2, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_all, which=3, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_all, which=4, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=1)
```

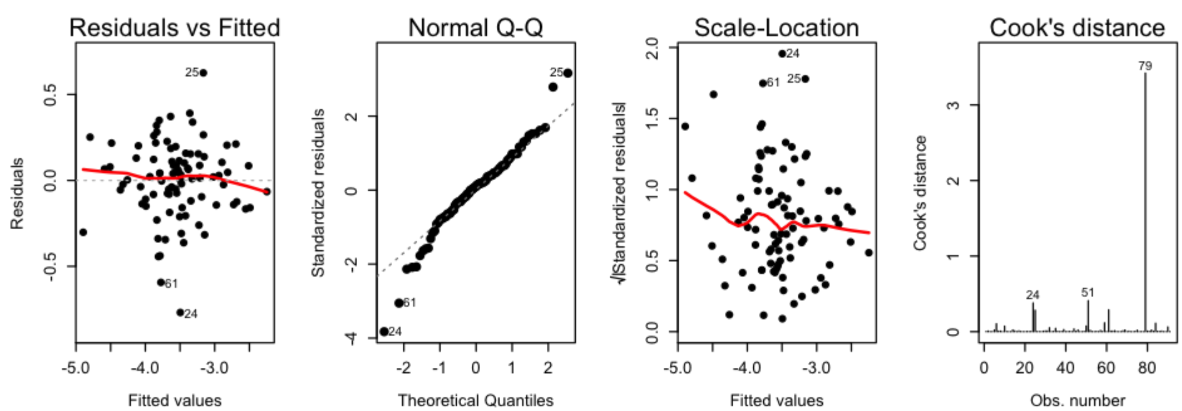


Figure 8: Diagnostic plots for model with only key explanatory variables

In [35]:
```
options(repr.plot.height = 3, repr.plot.width = 8, repr.plot.pointsize =
10)
par(mfrow = c(1,4))
plot(m_associated, which=1, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_associated, which=2, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_associated, which=3, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_associated, which=4, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=1)
```

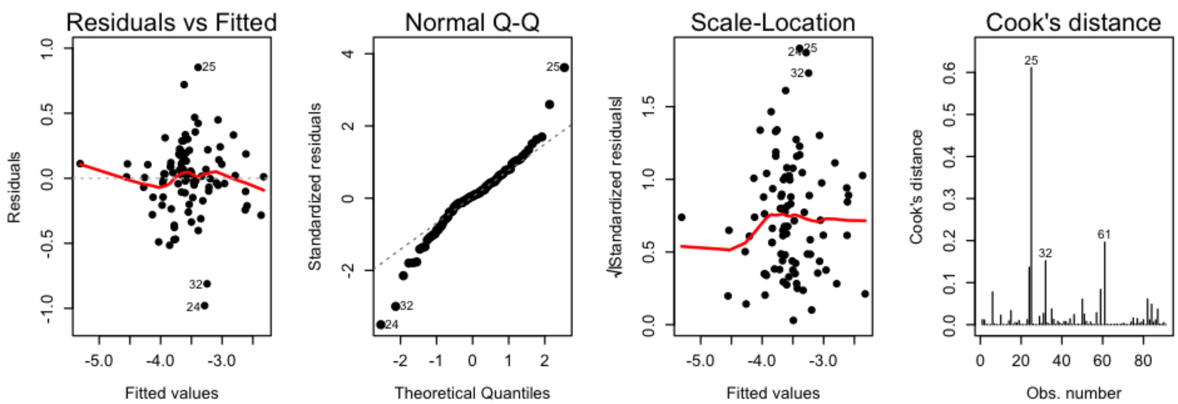
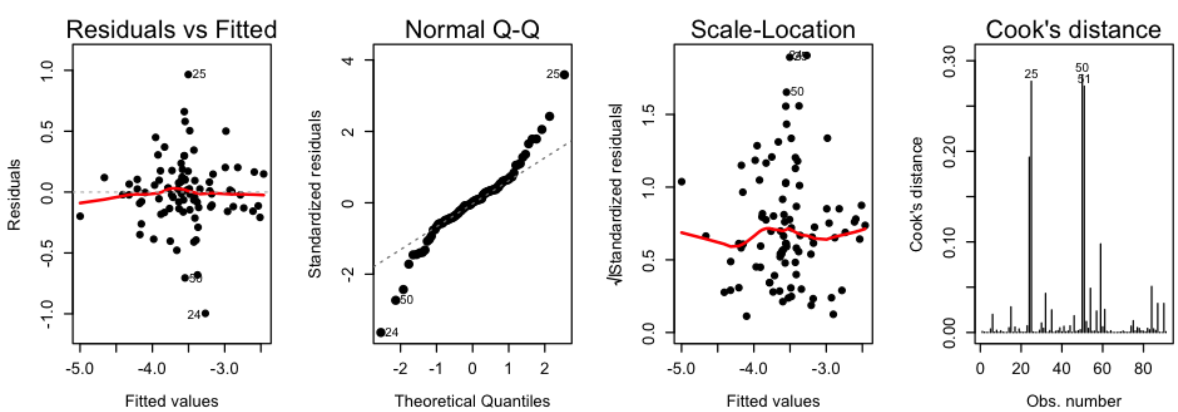


Figure 9: Diagnostic plots for most parsimonious model

In [36]:
```
options(repr.plot.height = 3, repr.plot.width = 8, repr.plot.pointsize =
10)
par(mfrow = c(1,4))
plot(m_key, which=1, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_key, which=2, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_key, which=3, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=2)
plot(m_key, which=4, pch=19, cex=1, cex.lab=1, cex.main=4, lwd=1)
```



Summary of diagnostic plots and assumptions for all three models (m_all,m_associated, and m_key)

1. **Linear in parameters**
   - As seen in our models above, all of our models are linear and additive in the parameters, the $\beta_0, \beta_1, \ldots \beta_k$
2. **Random sampling**
   - We assume that are n observations, $\{(x_{i1}, x_{i2}, \ldots, x_{ik}, y_i) : i = 1, 2, \ldots, n\}$ are independent and identically distributed, iid.
3. **No perfect collinearity**
   - As documented in the scatterplot matrices above (**Figs 3-6**) and those in the appendix, there is no *perfect* collinearity. Although, there are certainly explantory variables that are correlated, these variables are not *perfectly* correlated. $\therefore$ the explanatory variables are not redundant. The models we built and the inferences we draw therefrom do not suffer from the consequences of multicollinearity.
4. **Zero conditional mean**
   - The zero conditional mean assumption, $E(u|x_1, x_2, \ldots, x_k) = 0$ is not satisfied, *sensu stricto*, for any of the models presented above. The residual versus fitted values plots (**Figs 7-9**) document the extent to which these models violate this assumptions. If the zero mean assumption were satisfied then we should expect to see a horizontal red line, centered at zero. In contrast we see that our estimates of u, the residuals, are greater than expected for low fitted values for the first two models, but not for the last model where residuals are slightly smaller than expected.
5. **Homoskedasticity**
   - Homoskedasticity appears to be satisfied for all models presented above. Minor violations of this assumption can be observed in the residual versus fitted value plots (**Figs 7-9**) and the scale-location plots; however, in general, the variation about the fitted values are nearly constant across the range of values.
6. **Normality**
   - The assumption that the population error, u, is independent of the explanatory variables, $x_1, x_2, \ldots, x_k$ and is normally distributed appears to be satisfied for all models presented. Although we can not observe u, we can see that the standarized estimates of u, the standardized residuals, are nearly perfectly correlated with the theoretical quantiles expected under a normal distribution (**Figs 7-9**). The exception are the tails of the residual distribution which appear to slightly deviate from our expectations.

Discussion and Conclusions

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★ Discussion on 5-10 ommitted variables that may introduce bias.

- Estimate direction of bias (towards or away from 0) and, if possible, the size.
- Identify candidate surrogates for omitted variables.
- Synthesize findings to determine if effects are real or artifacts of ommitted variable bias.

Omitted Varibale Bias:

As we can see, our preferred model m_key includes several variables that have an effect on the crime rate (*wfed, prbarr, prbconv, pctmin80*). Moreover, the Adjusted $R^2 = 0.726$ indicates that nearly 73% of the variation in crime rate can be explained by the explanatory variables we have chosen for the model. Even in the all inclusive model m_all, the additional explanatory variables explain an additional 6.5% of variation in crime rate. This leaves 20% of the variation in crime unexplained due to variables we either cannot measure or have access to. Here we will discuss a few such possible variables,

- **Poverty :** In and of itself, higher poverty may not necessarily cause an increase in crime rates. However, poverty and the lack of steady income, especially at a level needed to cover basic living needs may drive individuals towards crime to make ends meet or acquire material items they may be able to access otherwise. While the dataset provides information on wage, it does not provide a benchmark of the poverty line, which would allow us to compare how the poverty from county to county. Moreover, impoverished communities tend to have less access to quality education and thus better careear opportunities which can otherwise lead to more financial stability. In this case, the poverty is most closely correlated (negatively) to the wages (higher poverty leads to lower wages) and postively correlated to crime rate (higher poverty leads to higher crime rates). Thus, by omitting poverty, we can potentially under estimate the impact of wages on crime rates
- **Education :** Education can have impact on crime rates as well in that better education leads to better and steady employment opportunities which can in turn impact income. Similar to poverty, education is positively correlated to the wages (higher edcuation leads to higher wages) and negatively correlated to crime rate (higher edcuation leads to lower crime rates). Thus, by omitting education, we can potentially under estimate the impact of wages on crime rates. By measuring the impact of education on crime rates, policies can be implemented to ensure proper funding and resources are given to improve education in disadvantaged communities. We should point out that in certain cases, highly education people will still commit common crimes though they may also commit other types of crimes such as tax fraud, embezzlement etc.
- **Type of crime :** We believe knowing the type of crime is an important factor that has not been captured. The 'Offense mix' variable is defined as the ratio of crimes involving "face-to-face" contact (such as robbery, assault and rape) to those that do not, but this variable does not give more granular information. As can be seen, $'mix'$ was dropped from the final model m_key. If we have capture the type of assualt in a factored variable, public officials can focus attention to specific solutions. e.g. if assaults involving a deadly weapon are most common, this could lead to policy changes involving better gun control or if sexual assault is the most pressing issue, then specific community outreach and educational programs may be introduced.
- **Day of week / Time of Day :** Knowing when and where crimes occur most frequently can help public safety officials plan effectively and better allocate resources. This missing variable can potentially bias the 'county' explanatory variable though the direction of the bias is a bit unclear.
- **Location :** Again, if we have better knowlegde of where the felonies are occuring (indoors / outdoors / type of location / intersection) can also help public safety officials curb crime by focusing on problem areas. e.g. if the data shows that criminal transactions are occuring at abandoned buildings more so than street intersections, policies can be implemented to better deal vacant properties, perhaps even convert them into spaces that postively impact the community. Again, this variable is potentially correlated to the 'county' variable.

The descrepancy between the coefficient of determination, R^2, for the nearly saturated model with all explanatory variables included ($R^2 = 0.791$) and the most parsimonious model($R^2 = 0.726$) is likely due to variety of sources and demands reconcilation. The full model includes all explanatory variables while the most parsimonious model includes 4 variables. It follows then that we accrue a $0.791 - 0.726 = 0.065 * 100 = 6.5\%$ increase in our ability to explain crime rate with the addition on 17 explanatory variables. Given that we can explain approximately 73% of the variation in crime rate with only 4 explainatory variables, the addition of 17 more explainatory variables to absorb 6.5% more variation in crime rate seems wasteful.

From a broader perspective, it is more reasonable to communicate policy recommendations to the campaign using a model comprised of 4 versus all explanatory variables. The media and public have limited cognitive bandwidth. To ask the politicians to reduce crime rate by juggling 9 predictors will be difficult enough, to include 11 more is ludicrous and beyond the scope of our goal.

Finally, from an economical perspective, why use the resources to explain and predict crime rate with all variables when models with comparable performance can be built with 4 variables? More important, by using these 4 variables, we could not only reduce the crime rate but also save the government resources to improve walfare, public services, senior care etc. If this study is to be repeated or reproduced elsewhere, we can save those investigators time, money, and ease of interpretation by only including the most salient explanatory variables.

Appendix

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Identify the independent variables which show significant contribution to crime rate

Does population density, tax revenue, and police force affect crime rate?

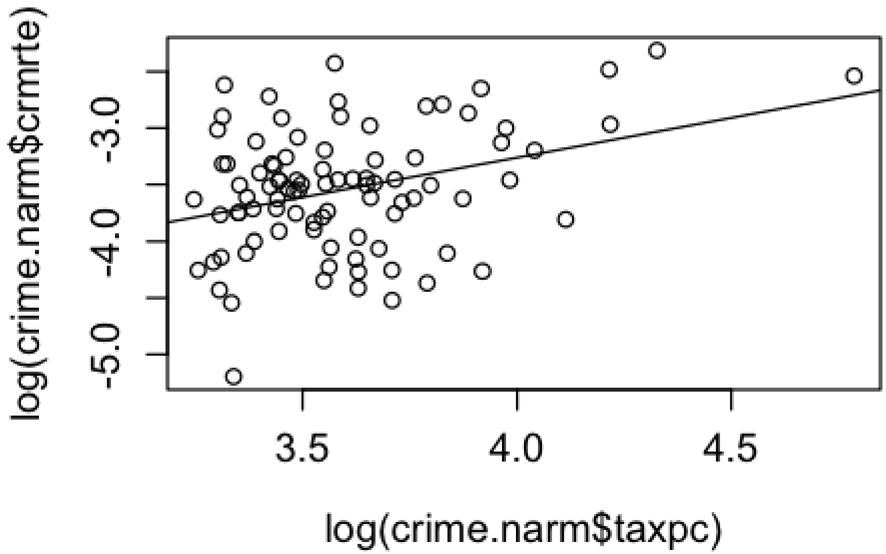
- Population, goverment income

In [37]:
```
# the explanatory variables of key interest
mp1 <- lm(log(crmrte) ~ log(density), data = crime.narm)
mp2 <- lm(log(crmrte) ~ log(polpc), data = crime.narm)
mp3 <- lm(log(crmrte) ~ log(taxpc), data = crime.narm)
```

In [38]:
```
# Compute robust standard errors
se.mp1 = sqrt(diag(vcovHC(mp1)))
se.mp2 = sqrt(diag(vcovHC(mp2)))
se.mp3 = sqrt(diag(vcovHC(mp3)))
# We pass the standard errors into stargazer through the se argument.
stargazer(mp1, mp2, mp3,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.mp1, se.mp2, se.mp3),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

```
============================================
                   Dependent variable:
             -------------------------------
                       log(crmrte)
                (1)        (2)        (3)
--------------------------------------------
log(density)   0.197
              (0.292)

log(polpc)                0.419
                         (0.472)

log(taxpc)                         0.705***
                                   (0.205)

Constant     -3.527***   -0.835   -6.081***
              (0.054)    (3.091)   (0.741)

--------------------------------------------
Observations    91         91         91
Adjusted R2    0.235      0.072      0.107
============================================
Note:          *p<0.05; **p<0.01; ***p<0.001
```

In [45]:
```
# check correlation between dependent variable and independent variables
options(repr.plot.height = 3, repr.plot.width = 4, repr.plot.pointsize =
10)
plot(log(crime.narm$taxpc), log(crime.narm$crmrte))
abline(mp3)
```



> In the category of population and goverment income, *taxpc* significantly affects crime rate with positive correlation.

Does income affect crime rate?

- Employee incomes

In [47]:
```
me1  <- lm(log(crmrte) ~ log(wcon), data = crime.narm)
me2  <- lm(log(crmrte) ~ log(wtuc), data = crime.narm)
me3  <- lm(log(crmrte) ~ log(wtrd), data = crime.narm)
me4  <- lm(log(crmrte) ~ log(wfir), data = crime.narm)
me5  <- lm(log(crmrte) ~ log(wser), data = crime.narm)
me6  <- lm(log(crmrte) ~ log(wmfg), data = crime.narm)
me7  <- lm(log(crmrte) ~ log(wfed), data = crime.narm)
me8  <- lm(log(crmrte) ~ log(wsta), data = crime.narm)
me9  <- lm(log(crmrte) ~ log(wloc), data = crime.narm)
```

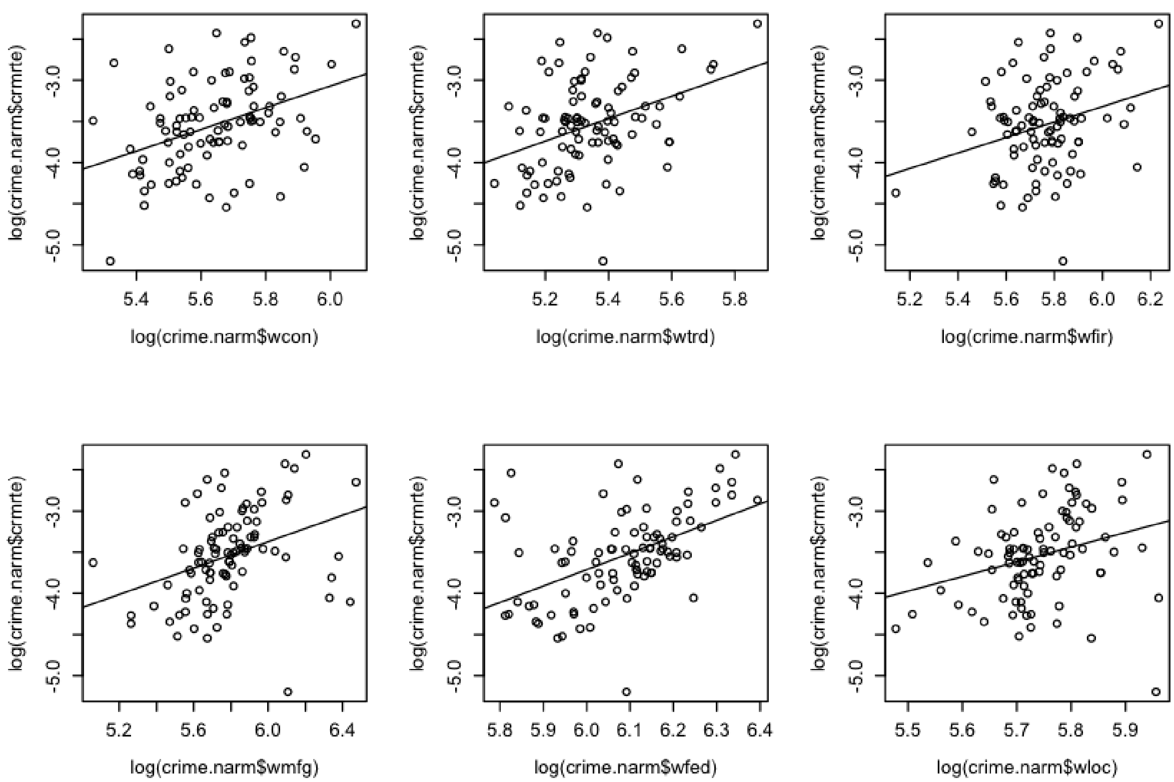
In [48]:
```
# Compute robust standard errors
se.me1 = sqrt(diag(vcovHC(me1)))
se.me2 = sqrt(diag(vcovHC(me2)))
se.me3 = sqrt(diag(vcovHC(me3)))
se.me4 = sqrt(diag(vcovHC(me4)))
se.me5 = sqrt(diag(vcovHC(me5)))
se.me6 = sqrt(diag(vcovHC(me6)))
se.me7 = sqrt(diag(vcovHC(me7)))
se.me8 = sqrt(diag(vcovHC(me8)))
se.me9 = sqrt(diag(vcovHC(me9)))
# We pass the standard errors into stargazer through the se argument.
stargazer(me1, me2, me3, me4, me5, me6, me7, me8, me9,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.me1, se.me2, se.me3, se.me4, se.me5, se.me6, se.m
e7, se.me8, se.me9),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

	Dependent variable:								
	log(crmrte)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(wcon)	1.321***								
	(0.396)								
log(wtuc)		0.559							
		(0.330)							
log(wtrd)			1.363***						
			(0.334)						
log(wfir)				0.940**					
				(0.350)					
log(wser)					0.089				
					(0.915)				
log(wmfg)						0.802**			
						(0.305)			
log(wfed)							1.997***		
							(0.473)		
log(wsta)								0.693	
								(0.459)	
log(wloc)									1.781*
									(0.885)
Constant	-10.993***	-6.902***	-10.826***	-8.960***	-4.039	-8.185***	-15.692***	-7.613**	-13.770**
	(2.237)	(1.974)	(1.790)	(2.012)	(5.040)	(1.746)	(2.900)	(2.692)	(5.054)
Observations	91	91	91	91	91	91	91	91	91
Adjusted R2	0.146	0.032	0.132	0.070	-0.009	0.116	0.240	0.012	0.077

```
Note:
*p<0.05; **p<0.01; ***p<0.001
```

In [50]:

```r
options(repr.plot.height = 5, repr.plot.width = 7, repr.plot.pointsize = 10)
par(mfrow = c(2,3))
plot(log(crime.narm$wcon), log(crime.narm$crmrte))
abline(me1)
plot(log(crime.narm$wtrd), log(crime.narm$crmrte))
abline(me3)
plot(log(crime.narm$wfir), log(crime.narm$crmrte))
abline(me4)
plot(log(crime.narm$wmfg), log(crime.narm$crmrte))
abline(me6)
plot(log(crime.narm$wfed), log(crime.narm$crmrte))
abline(me7)
plot(log(crime.narm$wloc), log(crime.narm$crmrte))
abline(me9)
```



In the category of employee income, *wcon*, *wtrd*, *wfir*, *wmfg*, *wfed*, and *wloc* significantly affect crime rate with positive correlation.

Do young males and the percent of population that is minority affect crime rate?

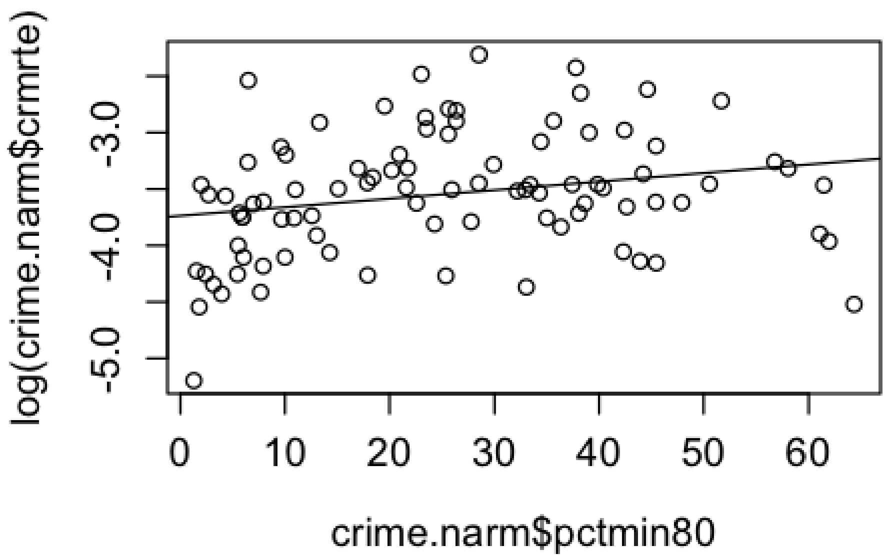
- minority and young male

In [51]:
```
mm1 <- lm(log(crmrte) ~ pctmin80, data = crime.narm)
mm2 <- lm(log(crmrte) ~ pctymle, data = crime.narm)
```

In [52]:
```
# Compute robust standard errors
se.mm1 = sqrt(diag(vcovHC(mm1)))
se.mm2 = sqrt(diag(vcovHC(mm2)))
# We pass the standard errors into stargazer through the se argument.
stargazer(mm1, mm2,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.mm1, se.mm2),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

```
============================================
                   Dependent variable:
             -------------------------------
                      log(crmrte)
                   (1)            (2)
--------------------------------------------
pctmin80          0.008*
                 (0.004)

pctymle                          6.529
                                (3.747)

Constant        -3.737***      -4.092***
                 (0.112)        (0.311)

--------------------------------------------
Observations       91             91
Adjusted R2       0.045          0.067
============================================
Note:          *p<0.05; **p<0.01; ***p<0.001
```

In [54]:
```
options(repr.plot.height = 3, repr.plot.width = 4, repr.plot.pointsize =
10)
plot(crime.narm$pctmin80, log(crime.narm$crmrte))
abline(mm1)
```



In the category of minority and young male, *pctmin80* significantly affects crime rate with positive correlation.

Does geographic location affect crime rate?

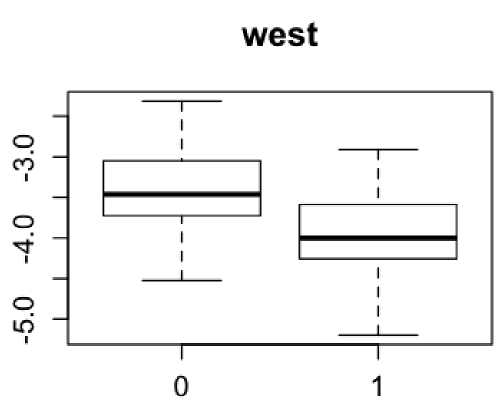
- geographic factors

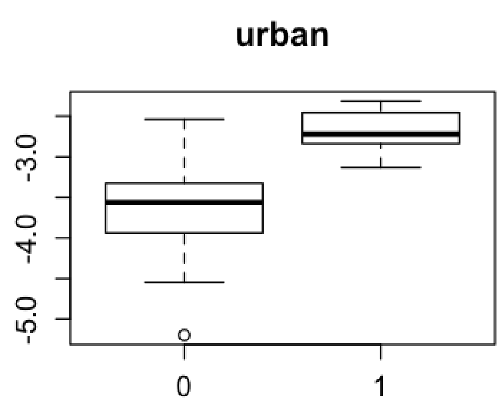
In [55]:
```
mg1 <- lm(log(crmrte) ~ factor(west), data = crime.narm)
mg2 <- lm(log(crmrte) ~ factor(central), data = crime.narm)
mg3 <- lm(log(crmrte) ~ factor(urban), data = crime.narm)
```

In [57]:
```
# Compute robust standard errors
se.mg1 = sqrt(diag(vcovHC(mg1)))
se.mg2 = sqrt(diag(vcovHC(mg2)))
se.mg3 = sqrt(diag(vcovHC(mg3)))
# We pass the standard errors into stargazer through the se argument.
stargazer(mg1, mg2, mg3,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.mg1, se.mg2, se.mg3),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

```
================================================
                       Dependent variable:
                   -----------------------------
                            log(crmrte)
                      (1)        (2)        (3)
------------------------------------------------
factor(west)1      -0.518***
                    (0.125)

factor(central)1               0.210
                              (0.117)

factor(urban)1                           0.944***
                                         (0.115)

Constant           -3.413***  -3.623***  -3.627***
                    (0.061)    (0.074)    (0.054)

------------------------------------------------
Observations          91         91         91
Adjusted R2         0.162      0.024      0.234
================================================
Note:               *p<0.05; **p<0.01; ***p<0.001
```

In [58]:
```
options(repr.plot.height = 3, repr.plot.width = 7, repr.plot.pointsize =
10)
par(mfrow = c(1,2))
plot(factor(crime.narm$west), log(crime.narm$crmrte), main = "west")
plot(factor(crime.narm$urban), log(crime.narm$crmrte), main = "urban")
```





> In the category of geographic factors, *west* significantly affects crime rate with negative correlation. On the other hand, *urban* significantly affects crime rate with positive correlation

Do outcomes of crime affect crime rate?

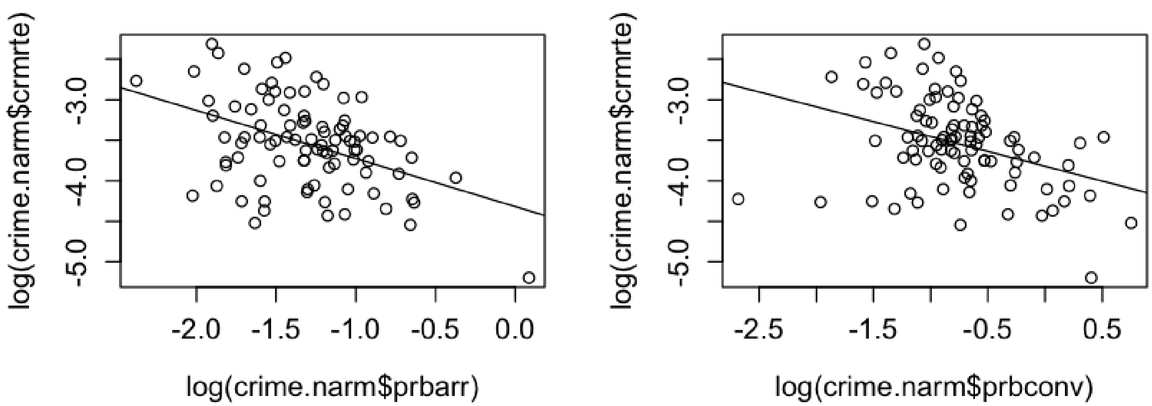
- crime outcomes

In [60]:
```
mc1 <- lm(log(crmrte) ~ log(prbarr), data = crime.narm)
mc2 <- lm(log(crmrte) ~ log(prbconv), data = crime.narm)
mc3 <- lm(log(crmrte) ~ log(prbpris), data = crime.narm)
mc4 <- lm(log(crmrte) ~ log(avgsen), data = crime.narm)
mc5 <- lm(log(crmrte) ~ log(mix), data = crime.narm)
```

In [61]:
```
# Compute robust standard errors
se.mc1 = sqrt(diag(vcovHC(mc1)))
se.mc2 = sqrt(diag(vcovHC(mc2)))
se.mc3 = sqrt(diag(vcovHC(mc3)))
se.mc4 = sqrt(diag(vcovHC(mc4)))
se.mc5 = sqrt(diag(vcovHC(mc5)))
# We pass the standard errors into stargazer through the se argument.
stargazer(mc1, mc2, mc3, mc4, mc5,
          type="text", keep.stat=c("n", "adj.rsq"),
          se = list(se.mc1, se.mc2, se.mc3, se.mc4, se.mc5),
          star.cutoffs=c(0.05, 0.01, 0.001)
         )
```

```
===============================================================
                              Dependent variable:
             --------------------------------------------------
                                 log(crmrte)
                (1)       (2)       (3)       (4)       (5)
---------------------------------------------------------------
log(prbarr)  -0.593***
              (0.155)

log(prbconv)           -0.367*
                       (0.158)

log(prbpris)                      0.169
                                 (0.287)

log(avgsen)                                 0.058
                                           (0.287)

log(mix)                                             0.0004
                                                     (0.114)

Constant     -4.318*** -3.820*** -3.390*** -3.672*** -3.543***
              (0.199)   (0.113)   (0.275)   (0.626)   (0.252)

---------------------------------------------------------------
Observations    91        91        91        91        91
Adjusted R2   0.180     0.130    -0.006    -0.010    -0.011
===============================================================
Note:                           *p<0.05; **p<0.01; ***p<0.001
```

In [63]:
```
options(repr.plot.height = 3, repr.plot.width = 7, repr.plot.pointsize =
10)
par(mfrow = c(1,2))
plot(log(crime.narm$prbarr), log(crime.narm$crmrte))
abline(mc1)
plot(log(crime.narm$prbconv), log(crime.narm$crmrte))
abline(mc2)
```



In the category of geographic factors, *prbarr* and *prbconv* significantly affect crime rate with negative correlation.

In [ ]: