Lab 3: Reducing Crime

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1. Introduction

As advisees to political campaigns for statewide office in North Carolina (NC), we believe that the crime rate across the state should be of central concern to any candidate. Local governments desire to control the crime rate, and rigorous data analysis is needed to understand the role of crime in different parts of the state. This report examines the available crime data and attempts to answer the following research question: What variables are associated with crime rates across counties in North Carolina? Based on this analysis, we generate several policy suggestions applicable to government officials in North Carolina for the late 1980s.

2. Data Definitions and Data Cleaning

The data analyzed in this report were collected as part of a multi-year study on crime by Cornwell and Trumball, originally published in 1994. The data include various factors potentially related to crime for 90 of the 100 counties in North Carolina. Because of legal limitations on access to the full dataset, this report will focus exculsively on the opensource data from 1987.

The dataset includes the following variables, which we present with definitions and assumptions:

county: An integer code indicating which NC county the row in the datafile represents. Review of relevant factors suggests that these are FIPS codes, which are standard county identification codes generated by the Environmental Protection Agency (see http://enacademic.com/dic.nsf/enwiki/49697 for details on FIPS codes for the state, including detailed maps).

year: A value of 1987 for all data points.

crmrte: The ratio of crimes committed per person, taken from the FBI's Uniform Crime Reports.

prbarr: The ratio of arrests to offenses, taken from the FBI's Uniform Crime Reports.

prbconv: The ratio of convictions to arrests. Arrest data is taken from the FBI's Uniform Crime Reports. Conviction data is taken from the North Carolina Department of Correction.

prbpris: The ratio of prison sentences to convictions, taken from the North Carolina Department of Correction.

avgsen: The average prison sentence in days. Although it is unspecified in the materials we received, we assume these data come from the North Carolina Department of Correction.

polpc: The police per capita, computed using the FBI's police agency employee counts.

density: The number of 100 people per square mile.

taxpc: The tax revenue per capita; we assume that this refers only to taxes assessed in units of $100 dollars at the state level or lower.

west: An indicator code specifying whether county is in Western North Carolina (1 if yes, 0 if no).

central: An indicator code specifying whether county is in Central North Carolina (1 if yes, 0 if no).

urban: An indicator code specifying whether county is urban, defined by whether the county is in a Standard Metropolitan Statistical Area as defined by the U.S. Census (see https://www.encyclopedia.com/finance/finance-and-accounting-magazines/standard-metropolitan-statistical-areas).

pctmin80: The percentage of population that belongs to a non-White racial group according to the 1980 U.S. Census.

mix: The ratio of face-to-face offenses (e.g., physical assault) to other offenses (e.g., automobile theft).

pctymle: The percentage of young males, defined as proportion of population that is male between the ages of 15 and 24, according to the 1980 U.S. Census data.

The remaining variables represent weekly wages in particular industries, as provided by the North Carolina Employment Security Commission:

wcon: construction

wtuc: transit, utilities, and communication

wtrd: wholesale, retail trade

wfir: finance, insurance, real estate

wser: service industry

wmfg: manufacturing

wfed: federal employees

wsta: state employees

wloc: local government employees

We start by evaluating the available data, cleaning it by removing anomolous values, and transforming relevant variables.

```
# Import the data
df = read.csv("crime_v2.csv")
```

In the original dataset, there are several variables, including *prbarr*, *prbpris*, and *pctymle* that represent probabilities and are given as decimal values between 0-1. To facilitate comparing the coefficients for these variables more easily with other numerical values in the dataset, we converted these to percentages between 0-100. We note that there is one county, Madison County (FIPS code 115), for which the *prbarr* value post-conversion is greater than 100%. This could reflect an error in data gathering or recording, but it may also reflect that it is common for indviduals in this county to be arrested with greater frequency than they commit specific offenses.

There is another "probability" factor, namely the probability of conviction after arrest (*prbconv*), for which several of the original values are greater than 1. Although this may seem anomalous, it reflects the fact that this factor is more effectively described as a ratio of the number of convictions per arrest, rather than as a probability of being convicted following arrest. Given that one might not be arrested for all crimes that one is subsequently convicted of, it makes sense that these numbers have a greater range than a traditional probabilities.

The variable *mix*, related to whether a crime is "face-to-face" or not, is also scaled in the original dataset with values between 0-1 in the original dataset. To facilitate the discussion of these data in tangible terms, we converted the values to values between 0-100 to make their scale more consistent with the rest of the data.

The variable *polpc* represents the number of police officers per known resident in a county, which is somewhat intangible on an individual scale. To address this, we converted the scores for this variable from number of police per capita in a county to number of police per 1000 residents of a county. That is, it is simply clearer to say, "There are 4 police officers per 1000 residents in X county" than "There is .004 of a police officer per resident of X county".

In the original dataset, the values for Wilkes Country (FIPS code 193) are given twice. We removed one set of these values so that they would not affect the overall analysis. In addition, there were six rows in the dataset that had no values for any variable. We assumed these rows were unintentionally included and removed all of them.

Data were not provided for the following counties (FIPS county codes are provide in parentheses): Camden (29), Carteret (31), Clay (43), Gates (73), Graham (75), Hyde (95), Jones (103), Mitchell (121), Tyrrell (177), and Yancey (199). We do not know why these cases were omitted from the original dataset, nor can we say the extent to which the omission of 1/10 counties across the state might affect the effectiveness of our recommendations. However, a review of 2012 population estimates for the omitted counties (see http://us-places.com/North-Carolina/population-by-County.htm) indicate that 9/10 are ranked between 86-100 of the 100 counties in overall population. The remaining omitted county is ranked 37th overall in population in the state and is close to several major metropolitan areas in the Northeast.

```
# Clean the data

## Reassign the dataframe to a working variable
df_calc <- df

# Convert the prbarr, prbpris, and pctymle variables from decimals to percentages
df_calc$prbarr <- df$prbarr * 100
df_calc$prbpris <- df$prbpris * 100
df_calc$pctymle <- df$pctymle * 100

# Convert the mix variable from decimals to percentage
df_calc$mix <- df$mix * 100

# Convert the polpc variable from decimals to number of police per 1000 people
df_calc$polpc <- df$polpc * 1000

# Convert the prbconv variable from integer to numeric
df_calc$prbconv <- as.numeric(levels(df$prbconv)[df$prbconv])
```

```
## Warning: NAs introduced by coercion
```

```
#remove row 89, which is a duplicate of row 88 (Madison County, FIPS 193)
df_clean <- df_calc[-c(89), ]

#remove rows with no data (i.e., all NA values)
df_clean <- df_clean[-c(91:97), ]
```

3. Building Models

Our central goal for this analysis is to determine what variables are most associated with crime across the state of North Carolina. For this reason, we will use the *crmrte* variable as the outcome variable for our first four models.

To begin, we examine the distribution of *crmrte* to determine its center and variability. This reveals that value of *crmrte* ranges from approximately 0.6% to 9.9%, with a mean of approximately 3.4%. There are 90 total cases and no missing cases.

```
summary(df_clean$crmrte)
```

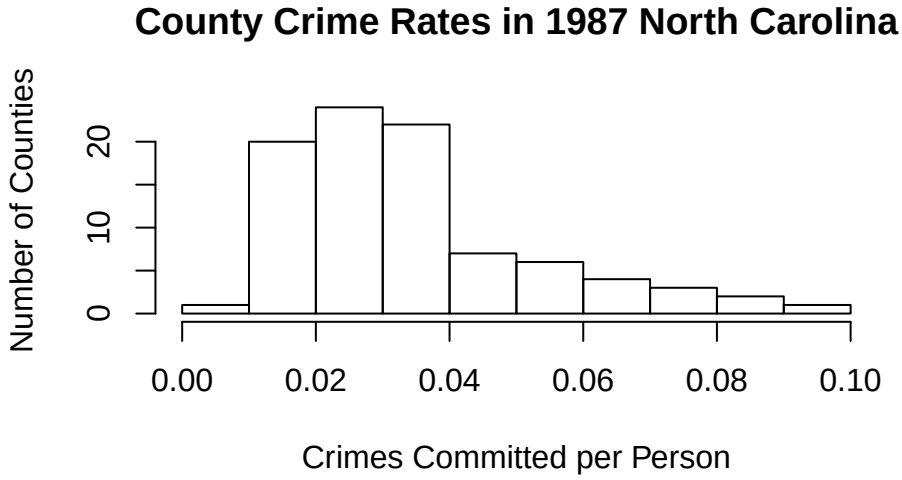
```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## 0.005533 0.020604 0.030002 0.033510 0.040249 0.098966
```

```r
length(df_clean$crmrte)
```

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

A histogram of the data reveals that the crime rate data are positively skewed, with the majority of counties having a crime rate between 1-4%. The extended right tail indicates that a few counties have substantially higher crime rates, with some between 8-10%.

```r
hist(df_clean$crmrte,
     main="County Crime Rates in 1987 North Carolina",
     xlab= "Crimes Committed per Person",
     ylab= "Number of Counties")
```



Due to the perceived severity of face-to-face crimes over non-face-to-face- crimes, we determined that a useful addendum to our research question would be: what are the factors associated with the face-to-face crime rate in North Carolina? We can find the face-to-face crime rate using the overall crime rate and the mix variable, which we recall contains the fraction of face-to-face crimes to other crimes. After making the fairly safe assumption that face-to-face + other = total crime, a somewhat tortuous manipulation gives us what we need: the ratio of face-to-face crimes among all crimes committed in a county.

$$\frac{\text{face-to-face}}{\text{total}} = 1 - \frac{\text{other}}{\text{total}} \tag{1}$$

$$= 1 - \frac{\text{other}}{\text{face-to-face} + \text{other}} \tag{2}$$

$$= 1 - \frac{1}{\frac{\text{face-to-face}+\text{other}}{\text{other}}} \tag{3}$$

$$= 1 - \frac{1}{\frac{\text{face-to-face}}{\text{other}} + 1} \tag{4}$$

$$= 1 - \frac{1}{\text{mix} + 1} \tag{5}$$

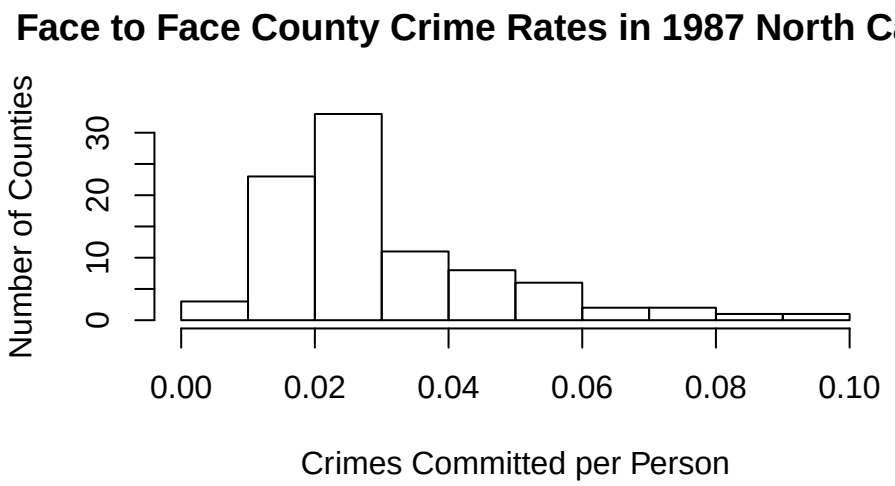
Now when multiplied with the overall crime rate, this gives the face-to-face crime rate in each county.

```r
# Calculate the face-to-face crime rate
df_clean$ftfcrmrte <- df_clean$crmrte * (1-1/(df_clean$mix+1))
```

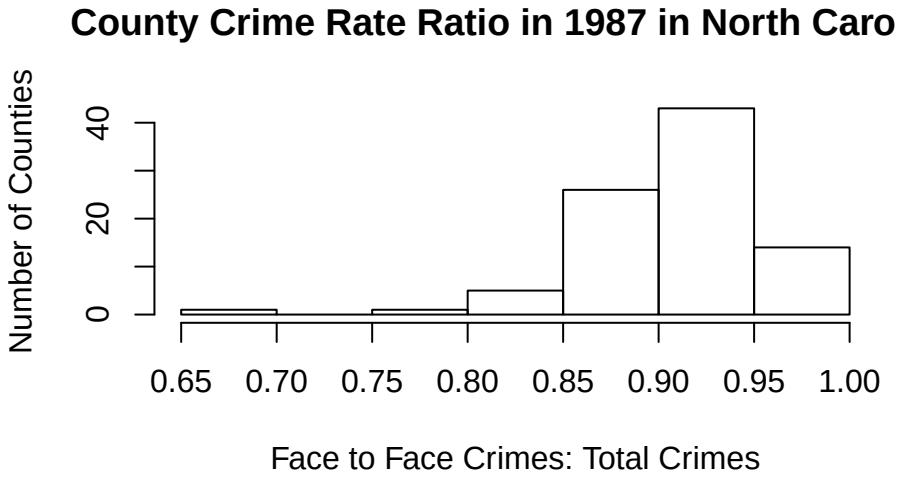
```r
# Examine the distribution
summary(df_clean$ftfcrmrte)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00503 0.01886 0.02692 0.03048 0.03649 0.09343
```

```r
hist(df_clean$ftfcrmrte,
     main="Face to Face County Crime Rates in 1987 North Carolina",
     xlab= "Crimes Committed per Person",
     ylab= "Number of Counties")
```




```r
df_clean$crmrte_ratio <- 1-1/(df_clean$mix+1)
hist(df_clean$crmrte_ratio,
     main= "County Crime Rate Ratio in 1987 in North Carolina",
     xlab= "Face to Face Crimes: Total Crimes",
     ylab= "Number of Counties")
```



The distribution of the face-to-face crime rate is similar, but not identical to, the base crime rate. The mean is lower, as we would expect, but only slightly lower, and values now range from 0.5% to 9.3%. The effect of this manipulation appears to be fairly small, so we will focus on the unadjusted crime rate for the majority of our analysis.

4. The Models

We model the factors contributing to crime rate in North Carolina in five stages, resulting in five related, but distinct, models.

The first four of our models are linear regressions of crime rate against an increasing numbers of predictive variables.

- Model 1 includes only the variables we believe to be the main predictors of crime rate: population density (*density*), tax per capita (*taxpc*), and percentage of young males in the population (*pctymle*).
- Model 2 includes the factors from Model 1 as well as several others that we believe contribute meaningfully to crime rate, including location in the state (*west*), the number of police per 1000 residents (*polpc*), the probability of being arrested (*prbarr*), and the probability of being convicted if arrested (*prbconv*), and the percentage of minorities (*pctmin80*).
- Model 3 builds on Model 2 by adding more information about the location of the county (*central*), the probability of getting a prison sentence (*prbpris*), and the average length of sentence (*avgsen*).
- Model 4 includes most available variables, even those of questionable merit.
- Model 5 is a regression of *crmrte* multiplied by the face-to-face crime rate, as determined using *mix*. To examine whether the causes of face-to-face crime might be different from the causes of crime overall, we will briefly examine this in a seperate model.

For each of these models, we expect a classic linear model with the following assumptions:

- Assumption 1: Linearity in parameters, such that each fit model has slope coefficients that are linear multipliers of the associated predictor variables.
- Assumption 2: Random sampling, such that the data points are independent and identically distributed. We have data for 90

To maintain interpretability, we did not transform the variables unless significant predictive gains were made.

4.1 Model 1

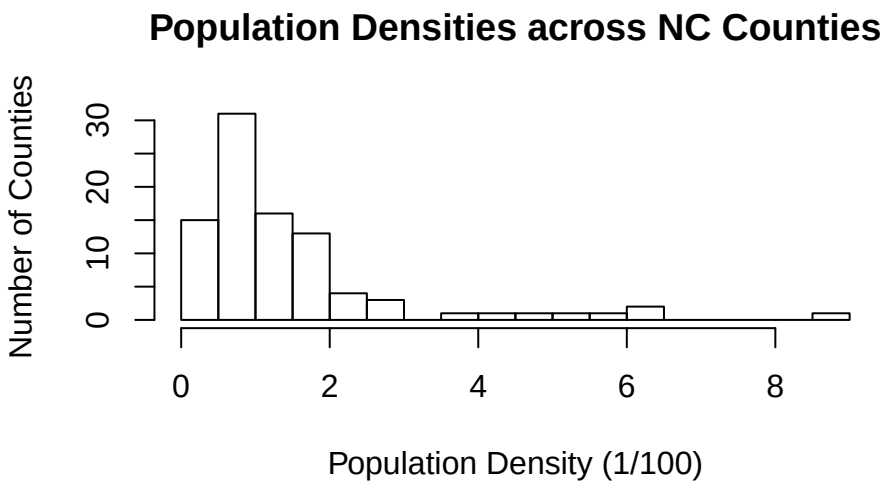
The current data suggest that population density, local tax per capita, and the percentage of young males in the population are strong predictors of crime. We evaluate each of these three predictor variables in turn.

Density:

```
summary(df_clean$density)
```

```
##     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00002 0.54718 0.97925 1.43567 1.56926 8.82765
```

```
hist(df_clean$density,
     main="Population Densities across NC Counties",
     xlab= "Population Density (1/100)",
     ylab= "Number of Counties",
     breaks = 15)
```



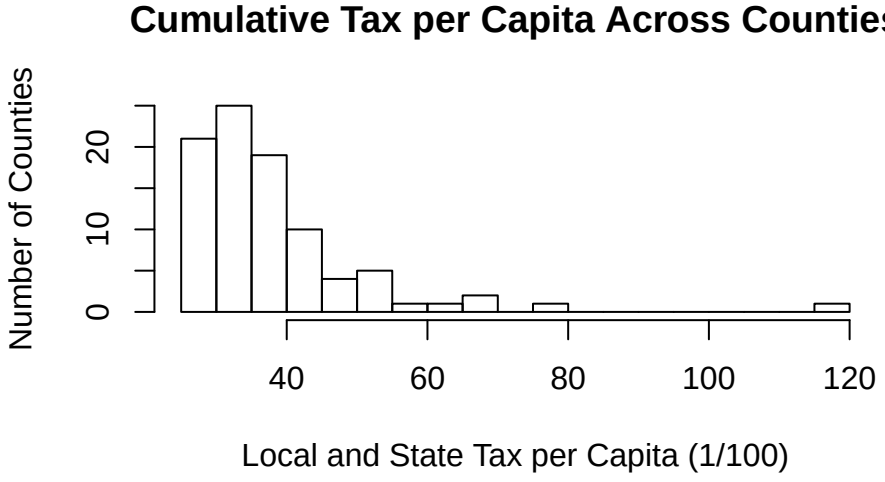
The value of density ranges from a score of approximately 0.002 to 880 people per square mile, with a mean of 145. The distribution of county densities is right skewed, with most counties having a score of 200 or fewer people per square mile.

Tax per Capita:

```
summary(df_clean$taxpc)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   25.69   30.73   34.92   38.16   41.01  119.76
```

```
hist(df_clean$taxpc,
     main="Cumulative Tax per Capita Across Counties",
     xlab= "Local and State Tax per Capita (1/100)",
     ylab= "Number of Counties",
     breaks = 30)
```



The cumulative value of taxes assessed at the local and state levels per capita ranges from $2,569 to $11,976 per year. Once again, we see a distribution that is right skewed, with revenue in most counties below the

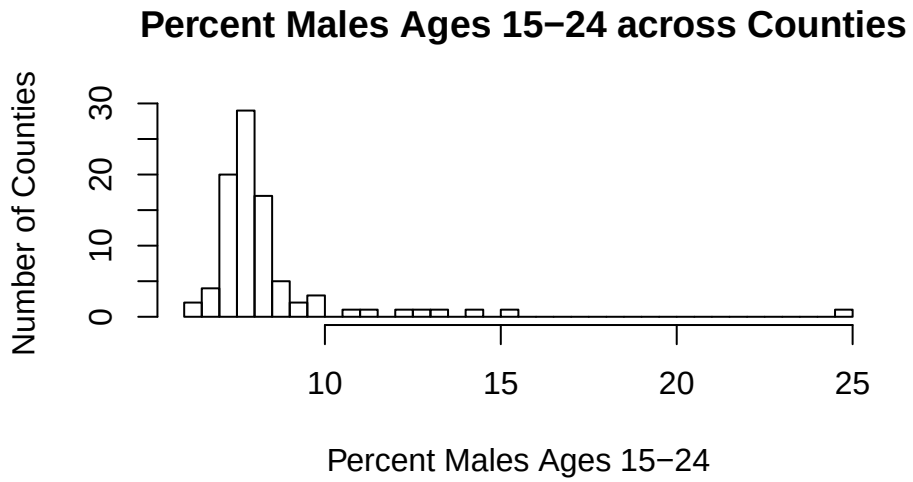
mean of $3,813 per year. The maximum value, the value for Dare county (FIPS 55) is nearly 50 % higher than the next closest value, suggesting that this county has an anomalously high tax rate for the state.

Percent Young Male:

```
summary(df_clean$pctymle)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   6.216   7.437   7.770   8.403   8.352  24.871
```

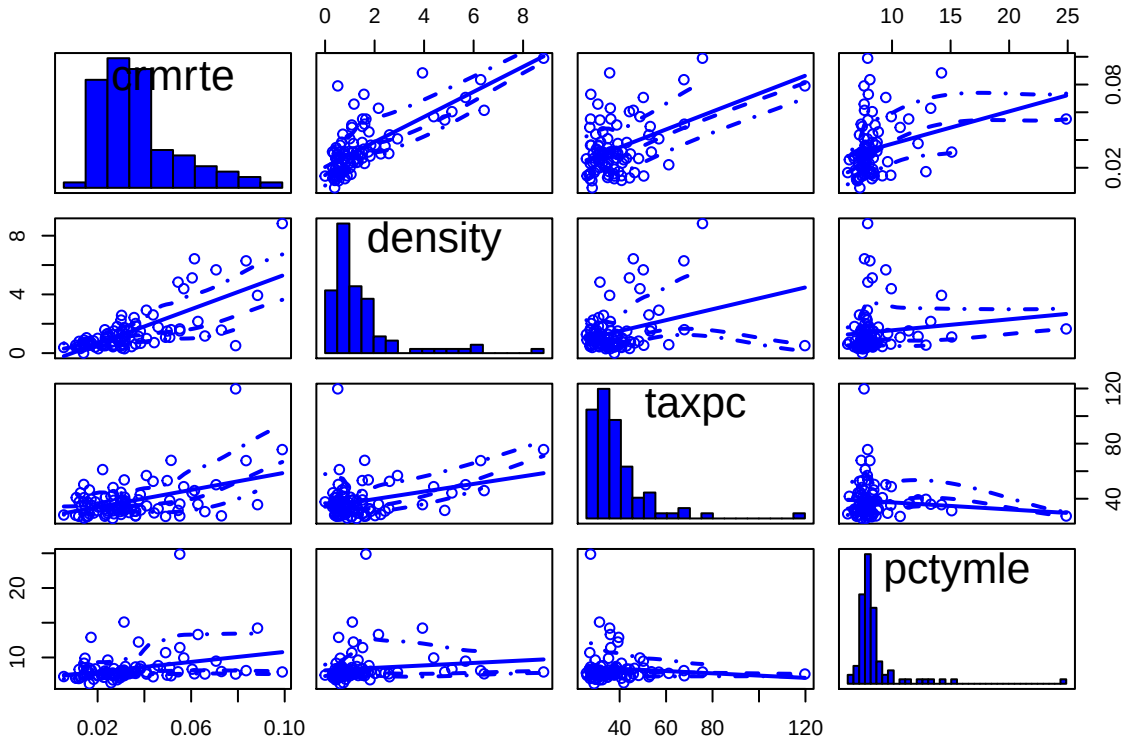
```
hist(df_clean$pctymle,
     main= " Percent Males Ages 15-24 across Counties",
     xlab= "Percent Males Ages 15-24",
     ylab= "Number of Counties",
     breaks = 30)
```



The percent of males between 15-24 years of age ranges from 6.2 to 24.9% across counties. Once again, we see a distribution that is right skewed, with the majority of counties having fewer than the average distribution of 8.4%. As with other primary variables, we see one extreme value: that for Onslow county (FIPS 133). This reflects that Onslow county includes the city of Jacksonville, recognized as the youngest county in the U.S. (see https://en.wikipedia.org/wiki/Jacksonville,_North_Carolina) in large part because it contains both the United States Marine Corps' Camp Lejeune and the New River Air Station, both of which are inhabited predominately by males under 25 years of age.

Before we build our model, we review the matrix of scatterplots of crime rate and the three variables evaluated above to identify any potential collinearity.

```
vars <- c("crmrte", "density", "taxpc","pctymle")
suppressWarnings(scatterplotMatrix(df_clean[,vars], diagonal = list(method= "histogram")))
```



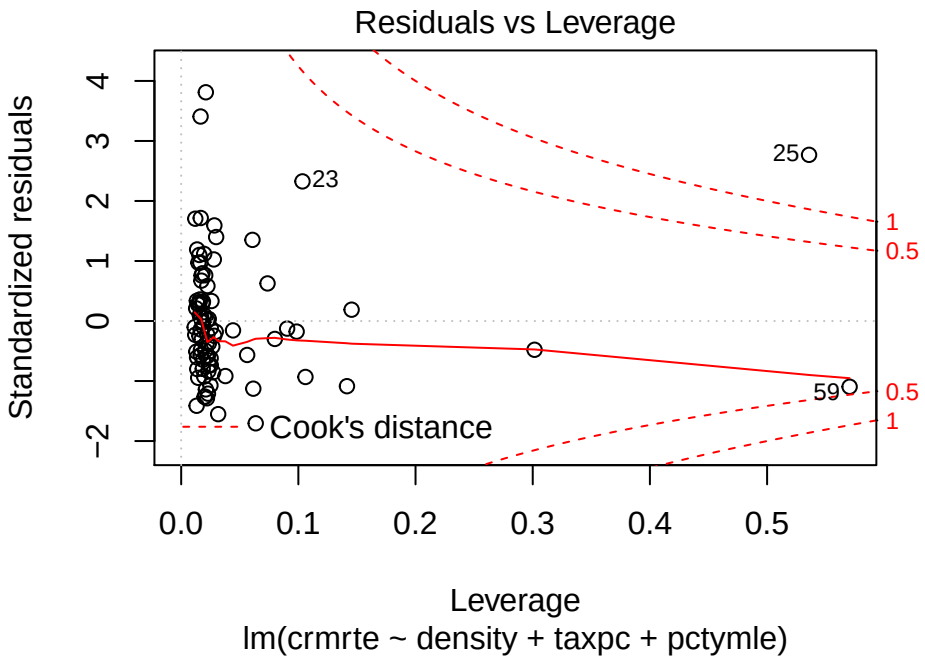
As we suspected, crime rate looks well predicted by each of the three primary variables selected as evidenced by the fairly strong positive slopes in the bivariate regressions in the scatterplot matrix. Additionally, though density and taxpc appear to have a positive correlation, none of the variables are collinear with any of the others, so we can make Assumption 3, no perfect collinearity.

With the evaluation of the variables complete, we build model 1, and evaluate the Cook's Distance for the residuals:

```
# Build Model 1
model_1 = lm(crmrte ~ density + taxpc + pctymle, data = df_clean)
summary(model_1)$r.square
```

```
## [1] 0.6404252
```

```
plot(model_1, which = 5)
```



We find one point that has a Cook's Distance greater than 1, Manteo county, but with no justification to remove it from the dataset, we simply note it. Of note, this county has the highest tax per capita, which could stem from its status as a tourist destination as the location of the Wright brothers' first flight.

Now that the model is built, we can validate Assumption 4, the exogeneity assumption. To do this, we check that the expectation of the fitted values times the residuals is 0 (the denominator does not matter for this calculation, so we just take the sum of fitted values times residuals).

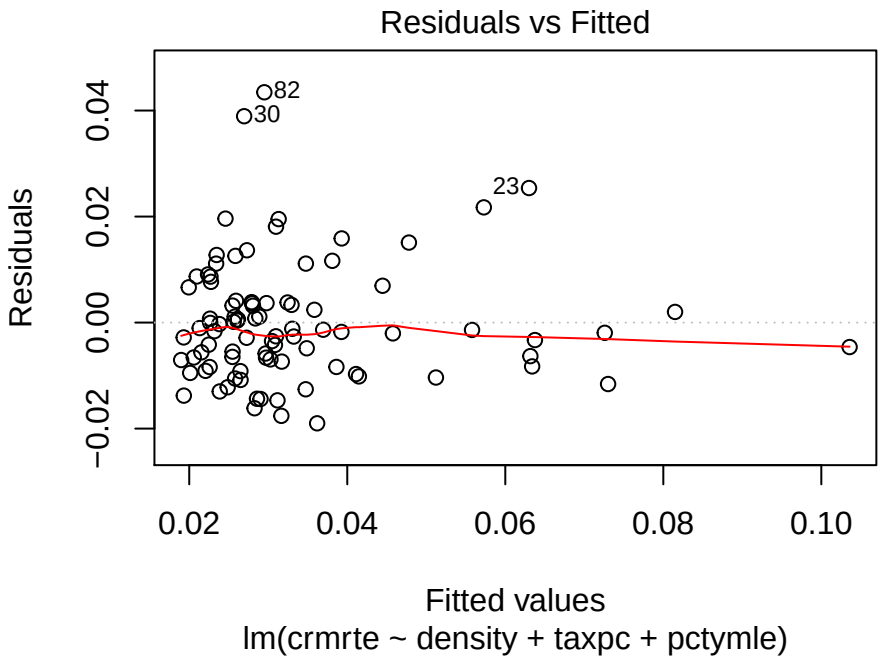
```
round(sum(model_1$residuals * model_1$fitted.values), 15)
```

```
## [1] 0
```

We find that the residuals times the fitted values sum to 0, validating Assumption 4.

To validate Assumption 5, homoskedasticity, we took a look at the residuals vs. fitted values plot and noted that the error range was relatively constant throughout the range of fitted values. This was difficult to validate because we have fewer data points at the higher values of crime rate than the lower values of crime rate.

```
plot(model_1, which = 1)
```



To validate assumption 6, the normality of the residuals, we looked at a Q-Q plot of the residuals, and noted the fairly straight line.

From the equation for model 1, we can see that all of these model coefficients are positive, indicating that for an increase in density, tax per capita, or percent young male, there is an associated increase in crime rate.

Density has an effect almost 4 times the size of percent young male, and an order of magnitude greater than tax per capita.

We can attempt to interpret our model in a way that helps us make policy suggestions for local governments in North Carolina. The increase in crime associated with increase in density makes sense intuitively, as we know that cities historically have more crime than rural areas. Higher population density means more people who can potentially come into conflict, and a greater sense of anonymity among people, which makes the potential social ramifications of committing crime lower. Politicians whose constituencies include high density areas should consider infrastructure projects that increase the livability and communal nature of cities in order to diminish the friction that accompanies living in close quarters. Improvements to affordable housing, public transportation, and public parks and recreation make tangible differences in the lives of urban dwellers, decreasing the risk that people will turn to crime out of economic desperation, and increasing the social cohesion that makes crime less likely.

Tax per capita shows an unexpected result. One might think that areas with lower tax revenue would have higher crime, but this is not the case. One potential explanation is that if tax revenue is positively correlated with the income of the county's inhabitants, with higher income meaning more tempting targets for crime. To test this, one might examine the wealth of victims of crime, to see if wealthier individuals are more likely to experience crimes. The importance of **socioeconomic diversity** as a potential omitted variable will be discussed in a later section. The observed effect be related to a reporting bias, since distrust of police and inaccesibilty of services may decrease the reporting of crime in low-income communities. A survey by an institution less culturally fraught might reveal that crime rates have been underreported in some communities, in which case these models could be recalculated with self-reported crime as the outcome variable. Finally, if tax revenue is *not* heavily correlated with income, then the causal arrow could actually point the other direction - that is, areas with higher crime rates impose higher taxes in order to fund the necessary responses

to crime (greater police forces, incarceration facilities, and repairing vandalism). Relevant omitted variables for further study would then include income per capita (discussed further on as **household earnings**) and overall tax rate.

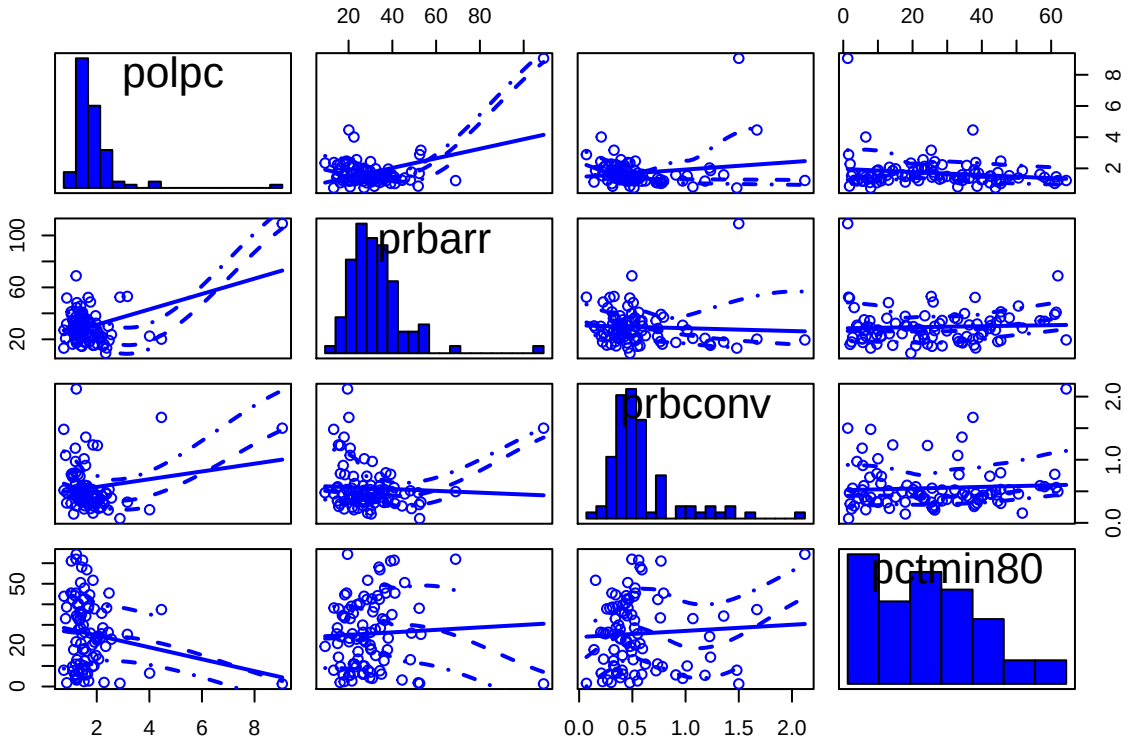
Further research, and particularly causal analysis, would be needed to determine whether an increase in the number of young men actually causes more crime, and demographic research could be done on arrest and conviction records to determine if young men are actually a disproportionate share of those found to be committing crime. We could imagine reasons why the hypothesis that young men cause crime fits with social background knowledge; we know there is immense social pressure connecting masculinity with wealth and the ability to provide for a family, as well as factors that socialize men to be more aggressive or violent. Local government officials would be wise to study the relationship between young men and crime further, with a particular eye towards the particular cultural dynamics in North Carolina that might be relevant. Policies that fund and promote arts and athletics for high school students, provide scholarships for higher education, and create work opportunities for young people should all be considered as opportunities that might deter young men from turning to crime.

4.2 Model 2

Model 2 includes *west*, *polpc*, *prbarr*, *prbconv*, and *pctmin80* in addition to the three variables from Model 1. During our EDA, we found that each of these had substantial correlations with the variable of interest, crime rate.

We conducted a full EDA on each of the explanatory variables, but for the sake of space, a simple matrix plot of the additional variables, other than *west*, is shown below. 24.4 % of all counties were labeled *west*.

```
vars <- c("polpc", "prbarr", "prbconv","pctmin80")
suppressWarnings(scatterplotMatrix(df_clean[,vars], diagonal = list(method = "histogram")))
```

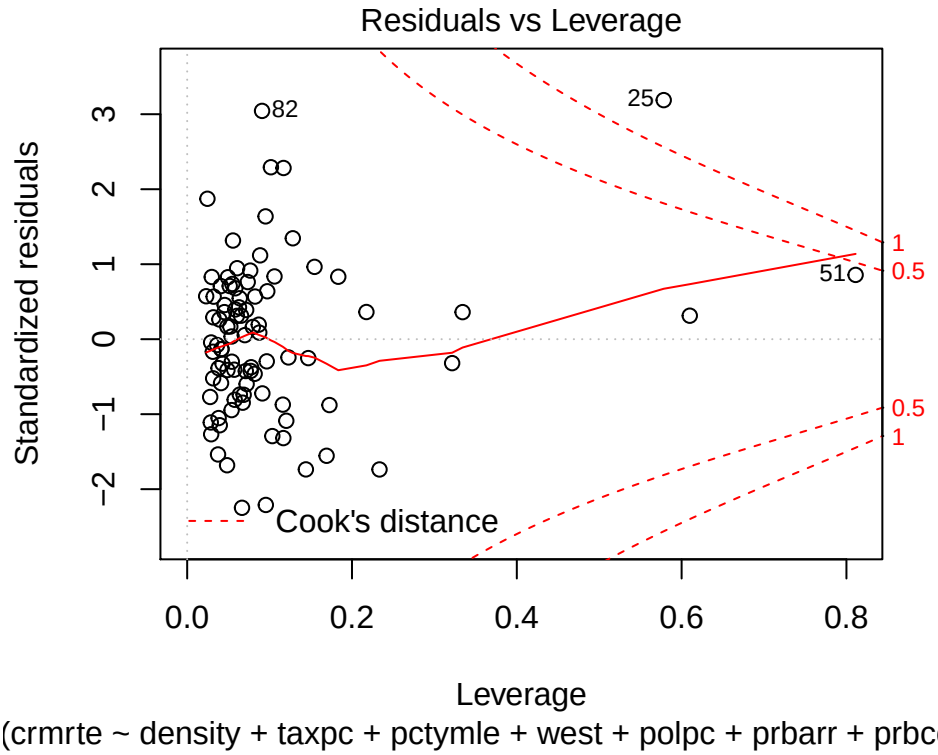


The matrix plot shows little correlation between most of the additional variables in this model, validating assumption 3, no perfect multicolinearity.

```
# Build Model 2
model_2 = lm(crmrte ~ density + taxpc + pctymle
             + west + polpc + prbarr + prbconv + pctmin80,
             data = df_clean)
summary(model_2)$r.square
```

```
## [1] 0.8240404
```

```
plot(model_2, which = 5)
```



Unsurprisingly, the R^2 increased from 0.64 to 0.82 with these additional 5 variables included. We also note that point 25 still has high leverage, just as in model 1. Perhaps we should study that county a bit more closely.

We also check Assumption 4, exogeneity, by summing the product of the residuals and fitted values and finding the sum of 0.

```
round(sum(model_2$residuals * model_2$fitted.values), 15)
```

```
## [1] 0
```

Assumptions 5 and 6 were validated for this model as they were for model 1.

Model 2, shown in the table in section 4.6 has positive coefficients for *density*, *taxpc*, *pctymle*, *polpc*, and *pctmin80* indicating that crime rate increases and these variables increase. On the other hand, the coefficients for *west*, *prbarr*, and *prbconv* are negative, indicating that crime rate decreases as these increase.

The additional coefficients in this model are somewhat more challenging to interpret than those in model

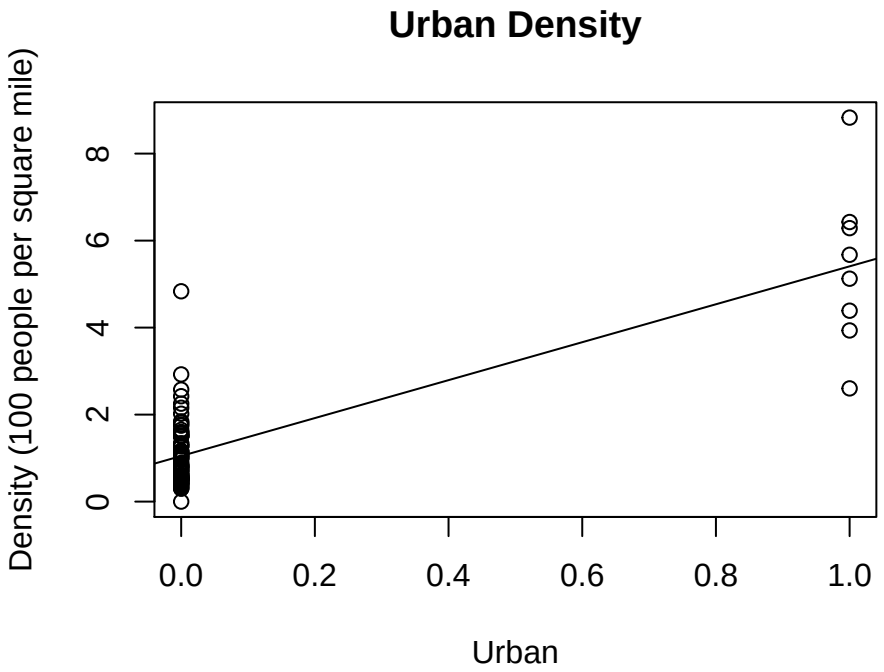
1. It seems unlikely that the longitude of a county would have a direct impact on its crime rate, and more likely that there is some omitted variable associated with crime that is more prevalent in Western counties. Additionally, the positive association between police per capita and crime is noteworthy. This association should be studied further, ideally with causal analysis, as there are plausible causal theories going in either direction. Perhaps heightened police presence creates an antagonistic relationship between officers and citizens, which leads to a distrust of authority and an increase in crime; the ideal way to test that would probably be to find counties with similar crime rates and other demographics where one county changes a policing policy and the other one doesn't, a natural paired experiment. However, it also seems possible that a county that experiences more crime would choose to up the size and acitivity of its police force in order to combat said crime; in this case, police records and government policy could probably help uncover this relationship. Local officials should pursue this line of research further to make informed policy decisions about policing.

The negative correlation between crime rate and both the probability of arrest and probability of conviction should also be studied further, with causal analysis as described above. It could be hypothesized that higher arrest and conviction rates deter crime. Alternatively, it could be hypothesized that when crime rate is lower, and fewer overall crimes are committed, it is easier to fully pursue all of the cases.

4.3 Model 3

For model 3, in addition to the variables from model 2, we added the remainder of the variables that we did not find problematic: *central*, *avgsen*, *prison*. These variables do not necessarily explain the crime rate well, but serve to show that model 2 gives a reasonable explanation of the observed crime rate. We excluded the urban variable because it is too closely related to density, as can be seen in this scatterplot:

```
plot(df_clean$urban , df_clean$density,
     main= "Urban Density",
     ylab= "Density (100 people per square mile)",
     xlab= "Urban")
abline(lm(density ~ urban, data = df_clean))
```



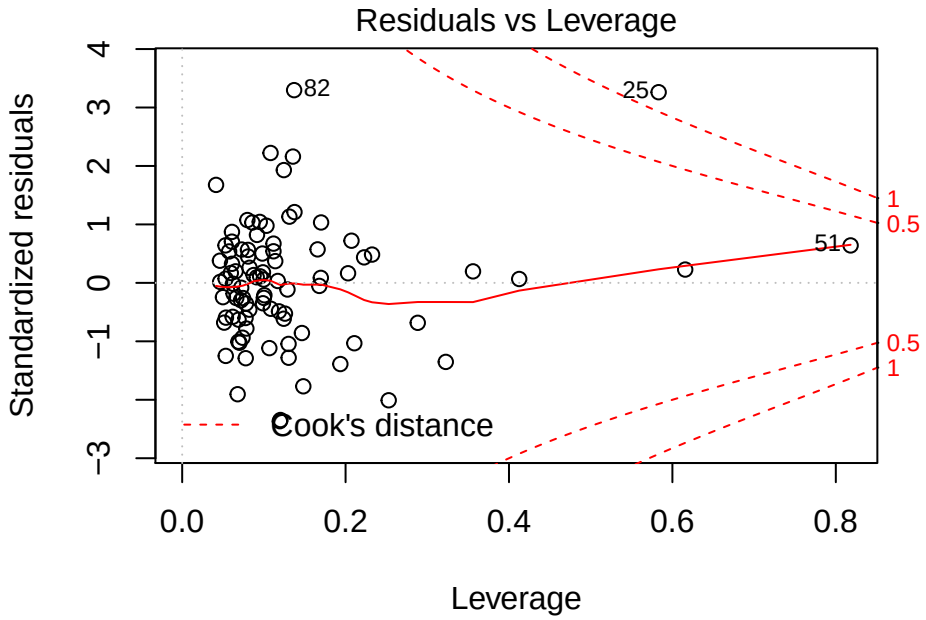
Excluded, are all of the wage variables because we cannot make any meaningful conclusions without a breakdown of what fraction of each county are involved in each profession.

With that, we build model 3:

```
# Build Model 3
model_3 = lm(crmrte ~ density + taxpc + pctymle
             + west + polpc + prbarr + prbconv + pctmin80
             + central + avgsen + prbpris,
             data = df_clean)
summary(model_3)$r.square
```

```
## [1] 0.8301355
```

```
plot(model_3, which = 5)
```



We note that point 25 is still exhibiting a Cook's distance of greater than 1.

Assumption 3 was tested by evaluating and eliminating the chance of any perfect collinearity between these variables.

To justify Assumption 4, we show that the sum of the residuals times the fitted values is 0:

```
round(sum(model_3$residuals * model_3$fitted.values), 15)
```

```
## [1] 0
```

Assumptions 5 and 6 were validated for this model as they were for models 1 and 2.

We note that the R^2 for this model, at 0.83, is negligibly better than the R^2 for model 2. This model, while interesting as an upper bound on what can reasonably be included in a model, should not be used to influence policy decisions.

4.4 Model 4

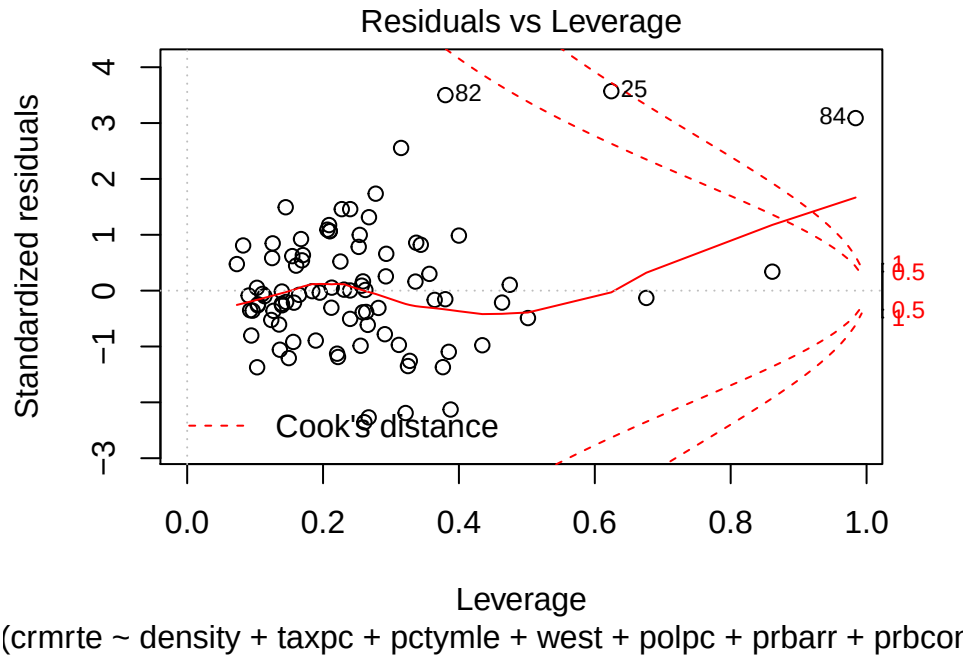
For this model, we included every variable available to us, simply to set an upper limit on the possible R^2. The resulting model is not a parsimonious one, and as such, we should not use it. However, it is interesting to note that the R^2 rises to 0.85, which is not much higher than model 3. Additionally, many points exceeding a Cook's distance of 1 are observed.

```
# Build Model 4
# model 4: kitchen sink. urban, wage.
model_4 = lm(crmrte ~ density + taxpc + pctymle
             + west + polpc + prbarr + prbconv + pctmin80
             + central + avgsen + prbpris
             + urban + wcon + wtuc + wtrd + wfir + wser
             + wmfg + wfed + wsta + wloc + mix,
             data = df_clean)
summary(model_4)$r.square
```

```
## [1] 0.8545586
```

```
plot(model_4, which = 5)
```

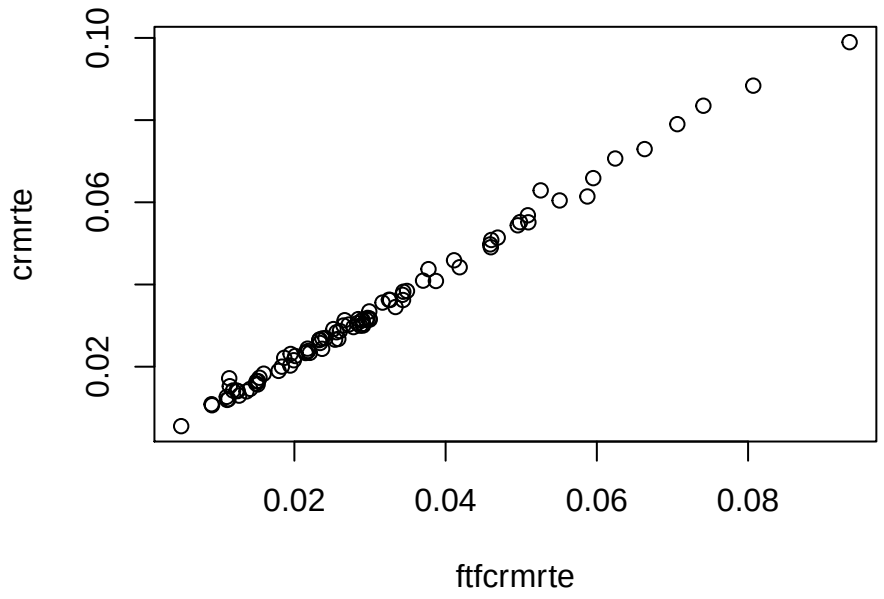
```
## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced

## Warning in sqrt(crit * p * (1 - hh)/hh): NaNs produced
```



4.5 Model 5

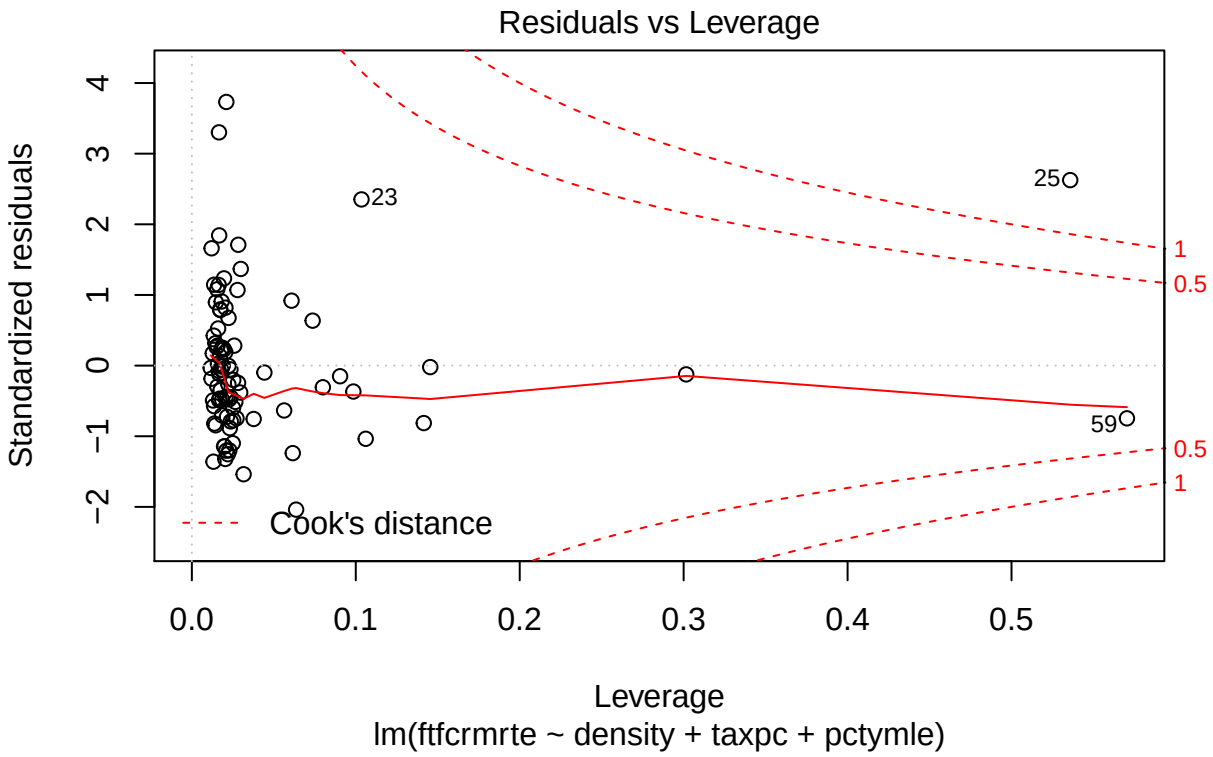
We repeated the analysis with the face to face crime rate as the dependent variable. However, results were not directionally different than the models shown above. This is unsurprising when the scatterplot of ftfcrmrte vs. crmrte is evaluated:

```r
plot(crmrte ~ ftfcrmrte, data = df_clean)
```



Therefore, we only share model 5, and do not use it for any policy recommendations.

```r
# Build Model 5
model_5 <- lm(ftfcrmrte ~ density + taxpc + pctymle, data=df_clean)
plot(model_5, which = 5)
```




```
summary(model_5)$r.squared
```

```
## [1] 0.6314511
```

This model is analogous to model 1, with face to face crime rate as the dependent variable. The coefficient magnitudes and signs are similar to model 1, and thus the interpretation and policy suggestions will all mirror section 4.1, and will not be restated here.

4.6 Model Summary

The models built above are summarized in **Table 4.6.1**.

```
stargazer(model_1, model_2, model_3, model_4, model_5, type = "latex",
          report = "vc", # Don't report errors, since we haven't covered them
          title = "4.6.1 Linear Models Predicting Crime Rate",
          keep.stat = c("rsq", "n"),
          omit.table.layout = "n") # Omit more output related to errors
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Fri, Jul 20, 2018 - 9:02:00 AM

5. Omitted Variables

While our models 1 and 2 do provide some useful information that can inform policy, there are a number of omitted variables that we did not have access to in this analysis that we suspect have meaningful associations

Table 1: 4.6.1 Linear Models Predicting Crime Rate

	Dependent variable:				
	crmrte				ftfcrmrte
	(1)	(2)	(3)	(4)	(5)
density	0.008	0.005	0.006	0.005	0.007
taxpc	0.0004	0.0002	0.0001	0.0002	0.0004
pctymle	0.002	0.001	0.001	0.001	0.002
west		−0.002	−0.005	−0.003	
polpc		0.007	0.007	0.007	
prbarr		−0.001	−0.001	−0.001	
prbconv		−0.019	−0.018	−0.019	
pctmin80		0.0003	0.0003	0.0003	
central			−0.004	−0.004	
avgsen			−0.0003	−0.0004	
prbpris			0.00004	0.00003	
urban				−0.0001	
wcon				0.00002	
wtuc				0.00001	
wtrd				0.00003	
wfir				−0.00004	
wser				−0.00000	
wmfg				−0.00001	
wfed				0.00003	
wsta				−0.00002	
wloc				0.00001	
mix				−0.0002	
Constant	−0.009	0.019	0.025	0.014	−0.007
Observations	90	90	90	90	90
R^2	0.640	0.824	0.830	0.855	0.631

with the crime rate. It is imperative that we name these variables and deduce the impact we believe they would have, or else we risk biasing our conclusions by considering only the variables we can measure.

We believe that **socioeconomic diversity** is likely to have a strong association with crime rate. If a county has a mix of people who have ample money and resources and people who have very little, there is likely to be social tension, and there is large opportunity for crime when populations who have abundant resources are in close proximity to others who need those resources desperately. We could measure socieconomic diversity by measuring the gap between the 1st and 3rd quartiles of household income. We would expect a large gap to be associated with a high crime rate, and we would also expect a positive correlation between our measured income gap and density, as dense urban areas tend to have both wealthy and impoverished people living in close proximity. In this case, omitted variable bias is positive, and the fitted values would be lower for a given density value if we had socioeconomic diversity as a variable.

We believe that the **unemployment rate**, as well as the **rate of citizens not participating in the labor force**, in a county would likely have a positive association with crime. When people are unable to earn a living, they may not have meaningful ways to spend their time, and they might struggle to pay their basic living expenses, both of which are scenarios that could be associated with crime. We might expect the correlation between unemployment and percent young male to be positive, as many young people are students or otherwise not participating in the labor force. Therefore, omitted variable bias is positive, and the fitted values would be lower for a given percent young male value if we had unemployment rate.

Additionally, we anticipate that **mean education level** for a county would likely have an impact on crime. If we added education level to a model, we would expect its coefficient to be negative, since when people have more education, they are more likely to have incomes and to contribute meaninfully to society, which seem like conditions that are unlikely to be related to crime. We anticipate a positive correlation between education level and density, since urban areas tend to have higher education levels due to job opportunities and presence of higher education institutions. Therefore, omitted variable bias for education level is negative, and the fitted values for a given value of density would likely be higher if we could control for education level.

We expect that **household earnings** would be negatively correlated with crime, since wealthier areas typically have less crime. We would expect correlation between household earnings and density to positive, because in salaries are typically higher in cities. Therefore, omitted variable bias is negative, and if we controlled for household earnings, the fitted values for a given density value would likely be higher.

The discussion of ommitted variables, however, is speculative, and should be reinforced with research, ideally randomized, controlled trials where possible.

WE SHOULD ALSO talk about the variables in our set we wanted to know more about: percentages of folks who fell in those different wage categories, better racial demographic detail, etc.

6. Conclusion

- might be worth making a point about county as unit : might make sense since county likely determines different police/judicial jurisdictions, but certain elements in our model might not be consistent across whole county (i.e. density, tax rate in cities, etc.)