Statistical Methods for Discrete Response, Time Series, and Panel Data (W271): Lab 4

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Instructions:

- **Due Date: 12/11/2018 (11:59 p.m. Pacific Time)**
- **Page limit of the pdf report: 20 (not include title and the table of content page**
- Use the margin, linespace, and font size specification below:
  - fontsize=11pt
  - margin=1in
  - line_spacing=single
- Submission:
  - Each group makes one submission to Github; please have one of your team members made the submission
  - Submit 2 files:
    1. A pdf file including the details of your analysis and all the R codes used to produce the analysis. Please do not suppress the codes in your pdf file.
    2. R markdown file used to produce the pdf file
  - Use the following file-naming convensation; fail to do so will receive 10% reduction in the grade:
    * FirstNameLastName1_FirstNameLastName2_FirstNameLastName3_LabNumber.fileExtension
    * For example, if you have three students in the group for Lab Z, and their names are Gerard Kelley, Steve Yang, and Jeffrey Yau, then you should name your file the following
      - GerardKelley_SteveYang_JeffreyYau_LabZ.Rmd
      - GerardKelley_SteveYang_JeffreyYau_LabZ.pdf
  - Although it sounds obvious, please write the name of each members of your group on page 1 of your pdf and Rmd files.
- This lab can be completed in a group of up to 3 students in your session. Students are encouraged to work in a group for the lab.
- For statistical methods that we cover in this course, use only the R libraries and functions that are covered in this course. If you use libraries and functions for statistical modeling that we have not covered, you have to provide (1) explanation of why such libraries and functions are used instead and (2) reference to the suppressWarnings(suppressMessages(library documentation. Lacking the explanation and reference to the documentation will result in a score of zero for the corresponding question.
- Students are expected to act with regards to UC Berkeley Academic Integrity.

Description of the Lab

In this lab, you are asked to answer the question **"Do changes in traffic laws affect traffic fatalities?"** To do so, you will conduct the tasks specified below using the data set *driving.Rdata*, which includes 25 years of data that cover changes in various state drunk driving, seat belt, and speed limit laws.

Specifically, this data set contains data for the 48 continental U.S. states from 1980 through 2004. Various driving laws are indicated in the data set, such as the alcohol level at which drivers are considered legally intoxicated. There are also indicators for "per se" laws—where licenses can be revoked without a trial—and seat belt laws. A few economics and demographic variables are also included. The description of the each of the variables in the dataset is come with the dataste.

Introduction

Over the years indiviual states have enacted many laws to to help prevent car accident deaths ranging from restricting driver alcohol intake to mandating seatbelts for passengers. These laws have been effective to vary degrees and have often corresponded with demographic changes that make effects more difficult to parse. Determing the effectiveness of driving laws has far reaching policy implications.

Exercises:

1. Load the data. Provide a description of the basic structure of the dataset, as we have done throughout the semester. Conduct a very thorough EDA, which should include both graphical and tabular techniques, on the dataset, including both the dependent variable *totfatrte* and the potential explanatory variables. You need to write a detailed narrative of your observations of your EDA. *Reminder: giving an "output dump" (i.e. providing a bunch of graphs and tables without description and hoping your audience will interpret them) will receive a zero in this exercise.*

Initial Examination

```r
load("driving.RData")

# view data and count NA
head(data)
```

```
##   year state sl55 sl65 sl70 sl75 slnone seatbelt minage zerotol gdl bac10
## 1 1980     1    1    0    0    0      0        0     18       0   0     1
## 2 1981     1    1    0    0    0      0        0     18       0   0     1
## 3 1982     1    1    0    0    0      0        0     18       0   0     1
## 4 1983     1    1    0    0    0      0        0     18       0   0     1
## 5 1984     1    1    0    0    0      0        0     18       0   0     1
## 6 1985     1    1    0    0    0      0        0     20       0   0     1
##   bac08 perse totfat nghtfat wkndfat totfatpvm nghtfatpvm wkndfatpvm
## 1     0     0    940     422     236      3.20      1.437      0.803
## 2     0     0    933     434     248      3.35      1.558      0.890
## 3     0     0    839     376     224      2.81      1.259      0.750
## 4     0     0    930     397     223      3.00      1.281      0.719
## 5     0     0    932     421     237      2.83      1.278      0.720
## 6     0     0    882     358     224      2.51      1.019      0.637
##   statepop totfatrte nghtfatrte wkndfatrte vehicmiles unem perc14_24
## 1  3893888     24.14      10.84       6.06   29.37500  8.8      18.9
## 2  3918520     24.07      11.08       6.33   27.85200 10.7      18.7
## 3  3925218     21.37       9.58       5.71   29.85765 14.4      18.4
```

```
## 4  3934109     23.64      10.09       5.67    31.00000 13.7      18.0
## 5  3951834     23.58      10.65       6.00    32.93286 11.1      17.6
## 6  3972527     22.20       9.01       5.64    35.13944  8.9      17.3
##   sl70plus sbprim sbsecon d80 d81 d82 d83 d84 d85 d86 d87 d88 d89 d90 d91
## 1        0      0       0   1   0   0   0   0   0   0   0   0   0   0   0
## 2        0      0       0   0   1   0   0   0   0   0   0   0   0   0   0
## 3        0      0       0   0   0   1   0   0   0   0   0   0   0   0   0
## 4        0      0       0   0   0   0   1   0   0   0   0   0   0   0   0
## 5        0      0       0   0   0   0   0   1   0   0   0   0   0   0   0
## 6        0      0       0   0   0   0   0   0   1   0   0   0   0   0   0
##   d92 d93 d94 d95 d96 d97 d98 d99 d00 d01 d02 d03 d04 vehicmilespc
## 1   0   0   0   0   0   0   0   0   0   0   0   0   0     7543.874
## 2   0   0   0   0   0   0   0   0   0   0   0   0   0     7107.785
## 3   0   0   0   0   0   0   0   0   0   0   0   0   0     7606.622
## 4   0   0   0   0   0   0   0   0   0   0   0   0   0     7879.802
## 5   0   0   0   0   0   0   0   0   0   0   0   0   0     8333.562
## 6   0   0   0   0   0   0   0   0   0   0   0   0   0     8845.614
```

```r
print(paste("The number of NA values in the dataset is ", sum(is.na(data))))
```

```
## [1] "The number of NA values in the dataset is  0"
```

```r
# variable definitions
desc
```

```
##        variable                                              label
## 1          year                                  1980 through 2004
## 2         state                   48 continental states, alphabetical
## 3          sl55                                  speed limit == 55
## 4          sl65                                  speed limit == 65
## 5          sl70                                  speed limit == 70
## 6          sl75                                  speed limit == 75
## 7        slnone                                     no speed limit
## 8      seatbelt          =0 if none, =1 if primary, =2 if secondary
## 9        minage                                minimum drinking age
## 10      zerotol                                  zero tolerance law
## 11          gdl                        graduated drivers license law
## 12        bac10                              blood alcohol limit .10
## 13        bac08                              blood alcohol limit .08
## 14        perse administrative license revocation (per se law)
## 15       totfat                             total traffic fatalities
## 16      nghtfat                           total nighttime fatalities
## 17      wkndfat                             total weekend fatalities
## 18    totfatpvm              total fatalities per 100 million miles
## 19   nghtfatpvm          nighttime fatalities per 100 million miles
## 20   wkndfatpvm            weekend fatalities per 100 million miles
## 21     statepop                                     state population
## 22    totfatrte            total fatalities per 100,000 population
## 23   nghtfatrte        nighttime fatalities per 100,000 population
## 24   wkndfatrte            weekend accidents per 100,000 population
## 25   vehicmiles                    vehicle miles traveled, billions
## 26         unem                            unemployment rate, percent
## 27    perc14_24              percent population aged 14 through 24
## 28     sl70plus                                  sl70 + sl75 + slnone
## 29       sbprim                            =1 if primary seatbelt law
## 30      sbsecon                          =1 if secondary seatbelt law
```

```
## 31          d80                              =1 if year == 1980
## 32          d81
## 33          d82
## 34          d83
## 35          d84
## 36          d85
## 37          d86
## 38          d87
## 39          d88
## 40          d89
## 41          d90
## 42          d91
## 43          d92
## 44          d93
## 45          d94
## 46          d95
## 47          d96
## 48          d97
## 49          d98
## 50          d99
## 51          d00
## 52          d01
## 53          d02
## 54          d03
## 55          d04                              =1 if year == 2004
## 56 vehicmilespc
```

Notes:

- There are 1200 pooled observations in the dataset, with each observation having 56 variables. There are no instances of NA values in the data, indicating that we have a balanced panel dataset.
- The variables can roughly be divided into several categories:
  1) Dummy variables hat indicate what laws are implemented in a particular state for a specific
  2) Dummy variables for each year in the panel.
  3) Continuous variables that measure fatality counts, and ratios of fatalities to the population. This includes our outcome variable of interest, `totfatrte`
  4) Continuous demographic variables like `unem` (state unemployment rate), `perc14_24` (percentage of population aged 14 to 24).
  5) "Index" variables that indicate which year and state the data corresponds to (aptly named `year` and `state`).

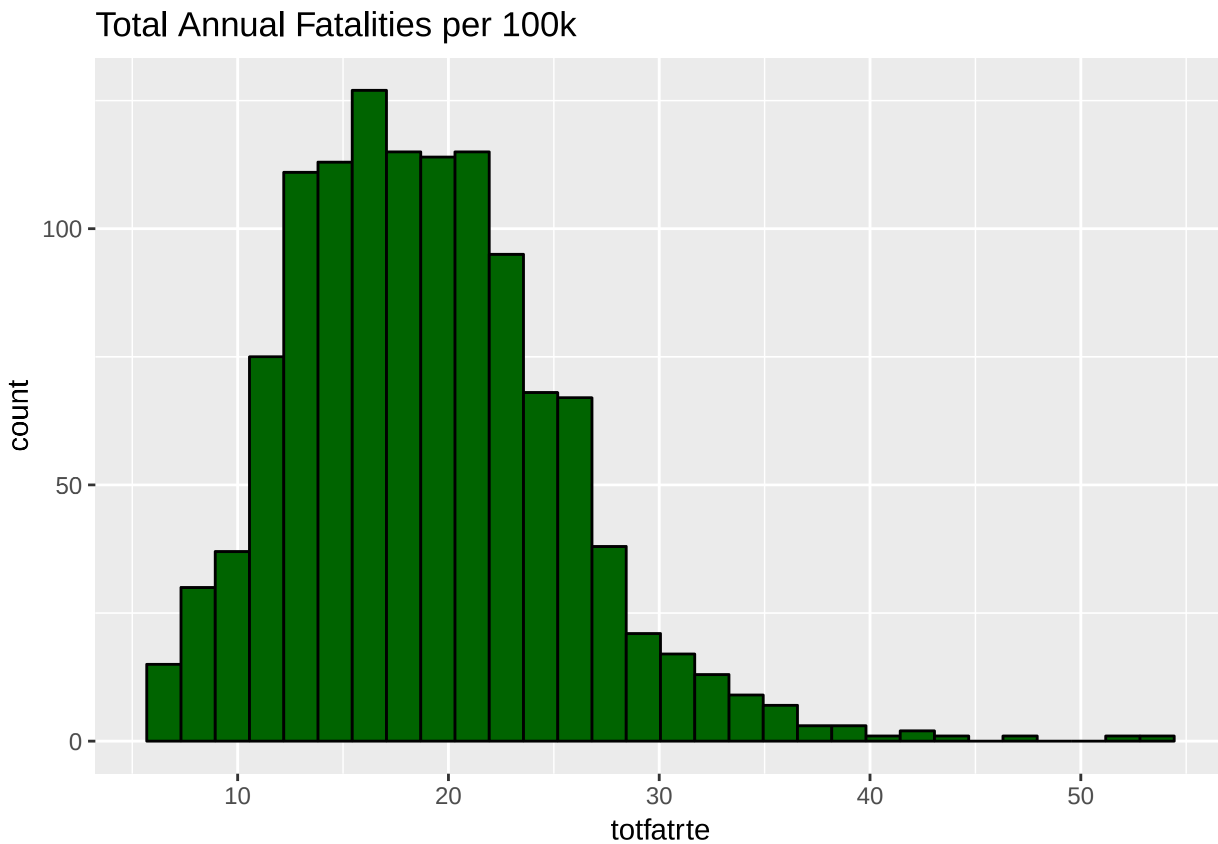
We'll examine these different variable types separately in our EDA.

Exploratory Data Analysis

Let's start by looking at our outcome variable, `totfatrte`. We'll plot a histogram of this variable:

```
ggplot(data, aes(x = totfatrte)) + geom_histogram(fill = "darkgreen",
    color = "black") + ggtitle("Total Annual Fatalities per 100k")
```

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



Observations:

- We see that the dataset is skewed right. This is typical of zero-bounded variables.
- There are a few cases where the fatalities are above 50 people per 100k. We will examine those in more detail to see if there's an explanation

Let's look at the outlier observations:

```r
cols.wo.yrdummies <- c("year", "state", "sl55", "sl65", "sl70",
    "sl75", "slnone", "seatbelt", "minage", "zerotol", "gdl",
    "bac10", "bac08", "perse", "totfat", "nghtfat", "wkndfat",
    "totfatpvm", "nghtfatpvm", "wkndfatpvm", "statepop", "totfatrte",
    "nghtfatrte", "wkndfatrte", "vehicmiles", "unem", "perc14_24",
    "sl70plus", "sbprim", "sbsecon")

t(data[data$totfatrte > 50, cols.wo.yrdummies])
```

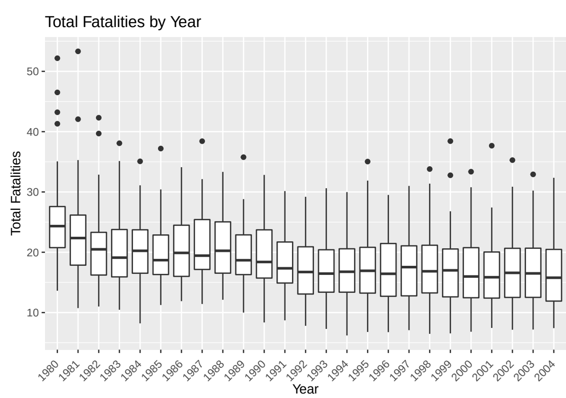
```
##                 1176      1177
## year         1980.00  1981.000
## state          51.00    51.000
## sl55            1.00     1.000
## sl65            0.00     0.000
## sl70            0.00     0.000
## sl75            0.00     0.000
## slnone          0.00     0.000
## seatbelt        0.00     0.000
## minage         18.00    18.000
## zerotol         0.00     0.000
## gdl             0.00     0.000
```

```
## bac10            0.00       0.000
## bac08            0.00       0.000
## perse            0.00       0.000
## totfat         245.00     264.000
## nghtfat        139.00     134.000
## wkndfat         58.00      68.000
## totfatpvm        4.90       5.056
## nghtfatpvm       2.78       2.566
## wkndfatpvm       1.16       1.302
## statepop    469557.00  491713.000
## totfatrte       52.18      53.320
## nghtfatrte      29.60      27.250
## wkndfatrte      12.35      13.830
## vehicmiles       5.00       5.222
## unem             4.00       4.100
## perc14_24       19.60      18.500
## sl70plus         0.00       0.000
## sbprim           0.00       0.000
## sbsecon          0.00       0.000
```

Both observations are in state 51 and occur in the early 1980s. It appears this state's 1980 population (~470k) is around 10% of the average state population that year (~4.67 million. This low state population could explain the large fatality ratios in those years. The other variables for this state in these years don't look particularly noteworthy.

Now lets look at total fatalities over time.

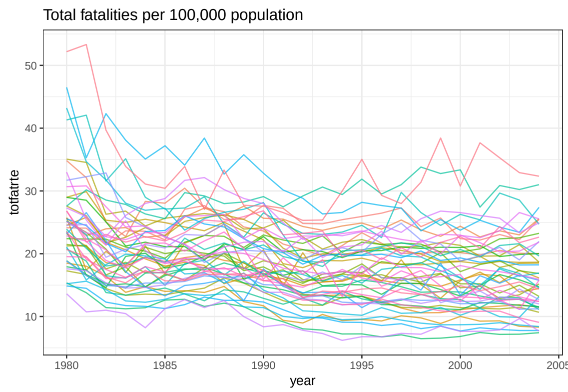
```r
ggplot(data, aes(as.factor(year), totfatrte)) + geom_boxplot() +
    ggtitle("Total Fatalities by Year") + xlab("Year") + ylab("Total Fatalities") +
    theme(axis.text.x = element_text(angle = 45, hjust = 1.2))
```



Total fatalities have declined gradually but not steadily since the 80s. However the variance across states remains fairly steady.

Let's see how the states are concentrated.

```r
# totfatrte: total fatalities per 100,000 population
ggplot(data, aes(x = year, y = totfatrte, colour = as.factor(state))) +
    geom_line(alpha = 0.7, show.legend = F) + ggtitle("Total fatalities per 100,000 population") +
    theme_bw()
```



The states are fairly concentrated and the outliers tend to fall on the high rather than the low side.

Let's now look at histograms for `perc14_24`, `unem`, and `vehicmilespc`:

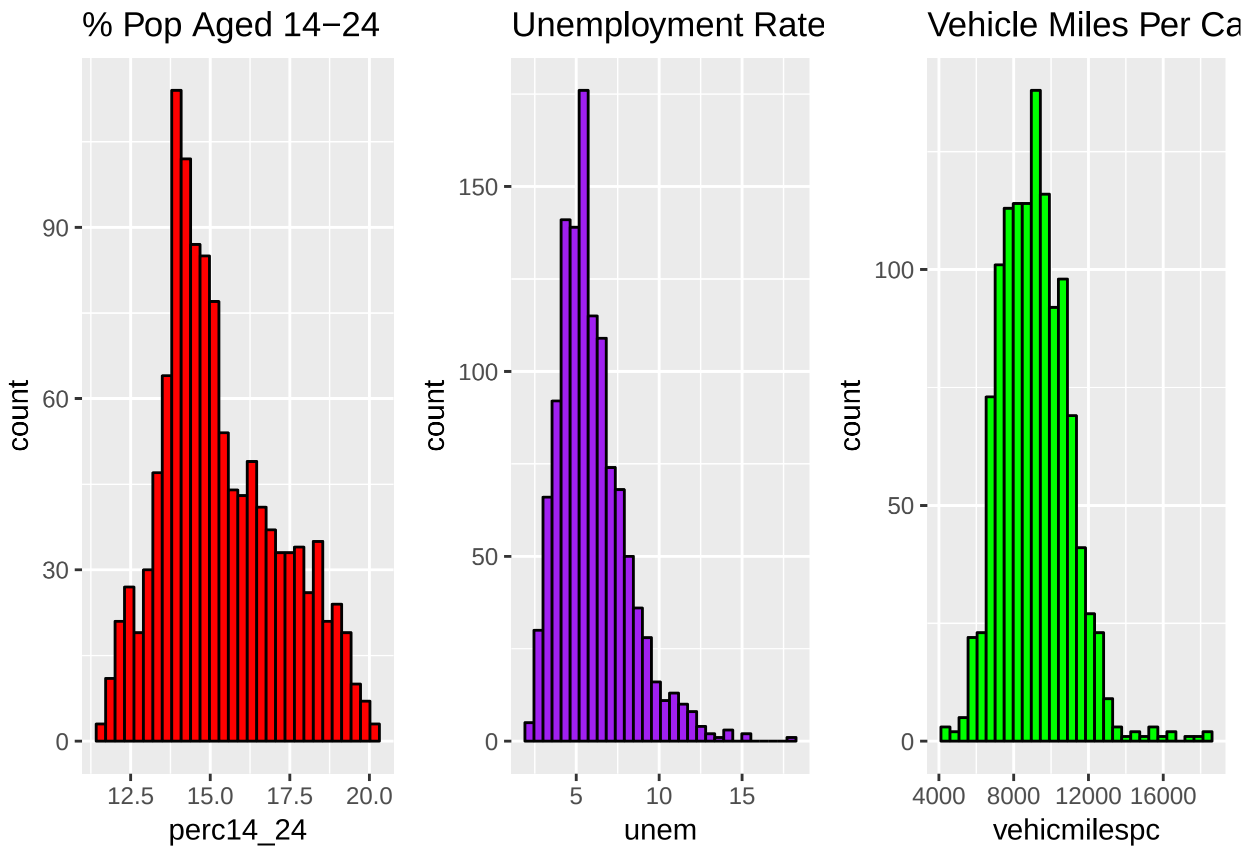
```
vehicpc.hist <- ggplot(data, aes(x = vehicmilespc)) + geom_histogram(color = "black",
    fill = "green") + ggtitle("Vehicle Miles Per Capita")

unem.hist <- ggplot(data, aes(x = unem)) + geom_histogram(color = "black",
    fill = "purple") + ggtitle("Unemployment Rate")

perc.hist <- ggplot(data, aes(x = perc14_24)) + geom_histogram(color = "black",
    fill = "red") + ggtitle("% Pop Aged 14-24")

grid.arrange(perc.hist, unem.hist, vehicpc.hist, ncol = 3, nrow = 1)
```

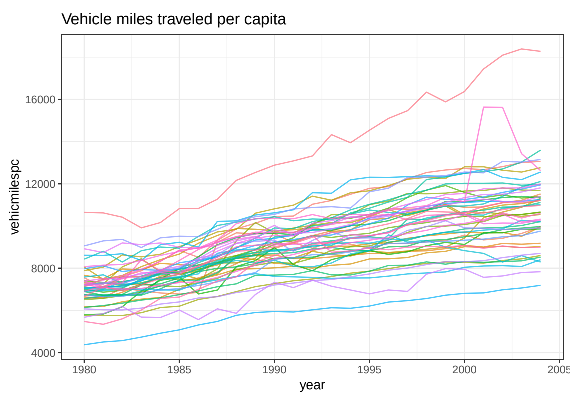
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



These distributions look fairly ordinary. Similar to the `totfatrte` histogram, we see right-ward skewness in the `unem` and `vehicmilespc`. Any other commentary. Maybe we can talk about log transforming these variables to deal with the skewness? Is this a good enough reason to log transform?

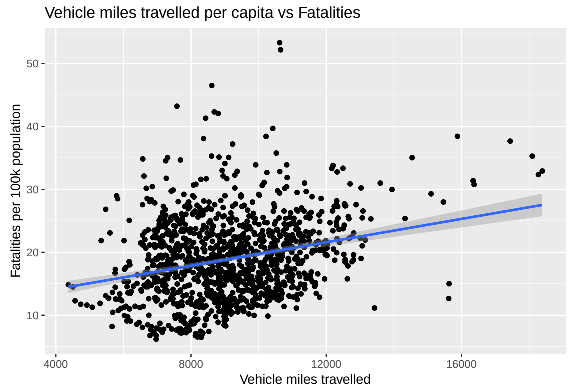
Questions I want to answer in the EDA: -Do these variables change over time? if not, comment how they'd be eliminated in the panel models unless we interact them with year. -Is there enough variance in them to be good candidate EVs in the model? -Does anything stick out as needing a transformation? e.g. rounding. Explain why this is a good idea.

```
# vehicmiles vehicle miles traveled, billions
ggplot(data, aes(x = year, y = vehicmilespc, colour = as.factor(state))) +
    geom_line(alpha = 0.7, show.legend = F) + ggtitle("Vehicle miles traveled per capita") +
    theme_bw()
```



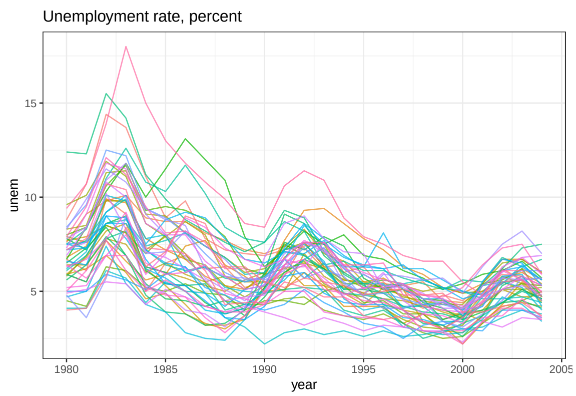
Miles traveled per capita have increased over time.

```r
ggplot(data, aes(x = vehicmilespc, y = totfatrte)) + geom_point() +
    geom_smooth(method = lm) + ggtitle("Vehicle miles travelled per capita vs Fatalities") +
    xlab("Vehicle miles travelled") + ylab("Fatalities per 100k population")
```



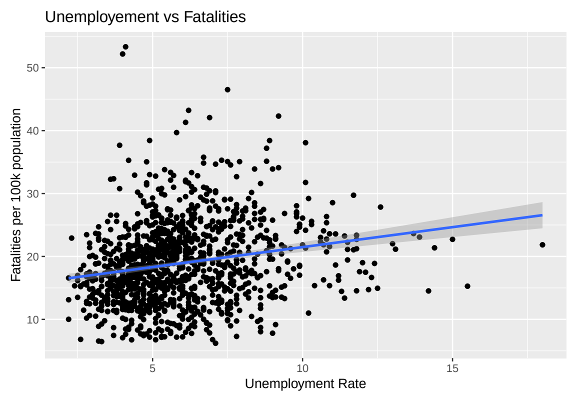
More miles travelled per capita correlates with more fatalities.

```r
# unem unemployment rate, percent
ggplot(data, aes(x = year, y = unem, colour = as.factor(state))) +
    geom_line(alpha = 0.7, show.legend = F) + ggtitle("Unemployment rate, percent") +
    theme_bw()
```



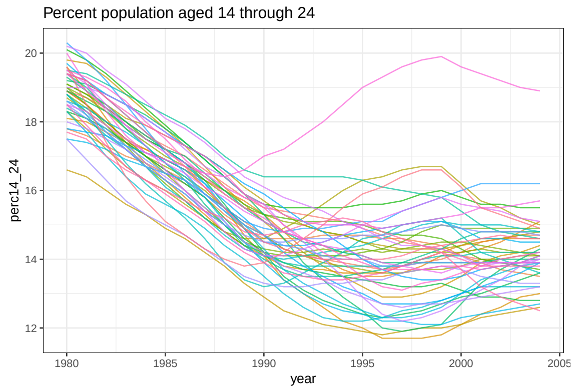
Unemployment peaked in early 80s followed by decrease until early 90s; steady decrease from mid 90s.

```r
ggplot(data, aes(x = unem, y = totfatrte)) + geom_point() + geom_smooth(method = lm) +
    ggtitle("Unemployement vs Fatalities") + xlab("Unemployment Rate") +
    ylab("Fatalities per 100k population")
```



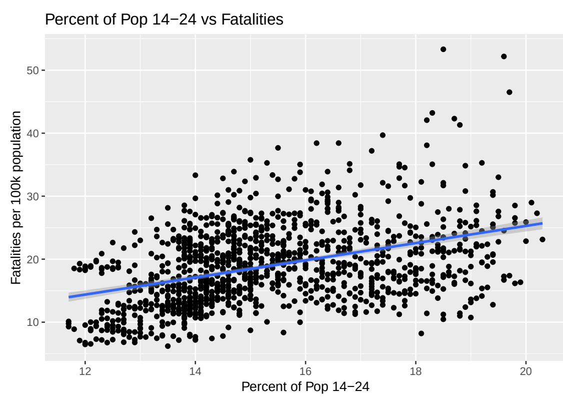
Higher unemployment correlates with more fatalities.

```
# perc14_24 percent population aged 14 through 24
ggplot(data, aes(x = year, y = perc14_24, colour = as.factor(state))) +
    geom_line(alpha = 0.7, show.legend = F) + ggtitle("Percent population aged 14 through 24") +
    theme_bw()
```



Rapid decrease in percent population aged 14 through 24 until early 90s; slight increase afterwards.

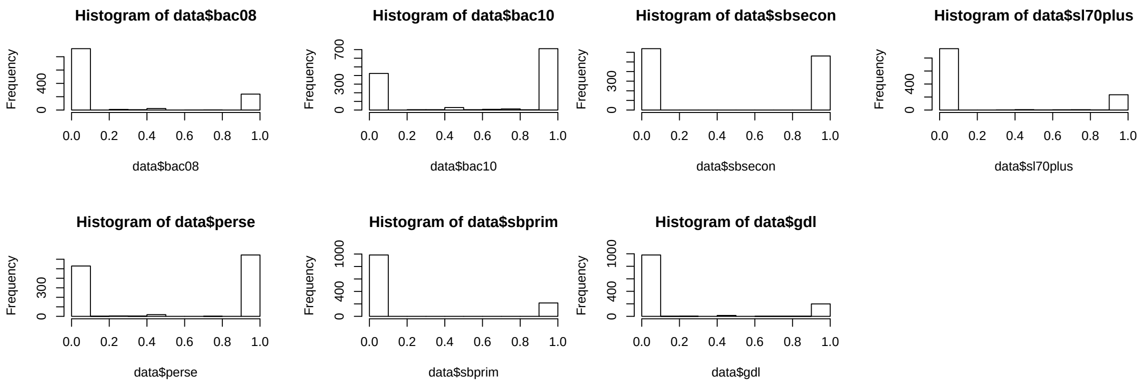
```
ggplot(data, aes(x = perc14_24, y = totfatrte)) + geom_point() +
    geom_smooth(method = lm) + ggtitle("Percent of Pop 14-24 vs Fatalities") +
    xlab("Percent of Pop 14-24") + ylab("Fatalities per 100k population")
```



Higher percent of population 14-24 correlates with more fatalities.

Next lets examine our binary variables.

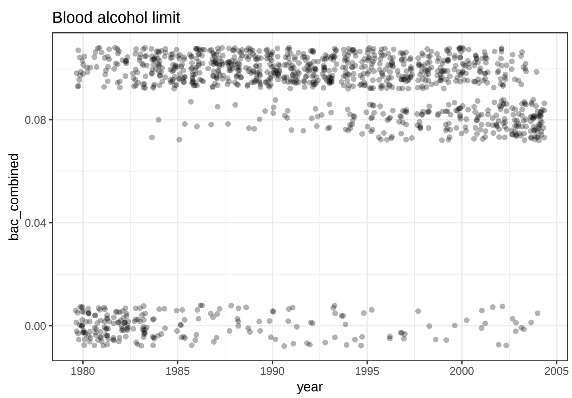
```
par(mfrow = c(2, 2))
hist(data$bac08)
hist(data$bac10)
hist(data$perse)
hist(data$sbprim)
hist(data$sbsecon)
hist(data$sl70plus)
hist(data$gdl)
```



Variables displays some degree of skewness and may need to transform. Additionally, some variables that appear to be binary have values between 0 and 1 to indicate mid year changes. We will round these variables.

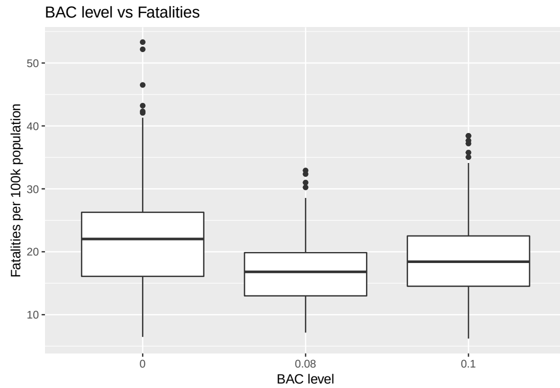
```
# if '1' in bac10, set as 0.1; else set as '0' or '1' in
# bac08
data$bac_combined <- ifelse(round(data$bac10) > 0, 0.1, 0.08 *
    round(data$bac08))
data$sl_combined <- ifelse(round(data$sl55) > 0, 55, ifelse(round(data$sl65) >
    0, 65, ifelse(round(data$sl70) > 0, 70, ifelse(round(data$sl75) >
    0, 75, 80))))
```

```
ggplot(data, aes(x = year, y = bac_combined, group = state)) +
    geom_jitter(alpha = 0.3) + theme_bw() + ggtitle("Blood alcohol limit")
```



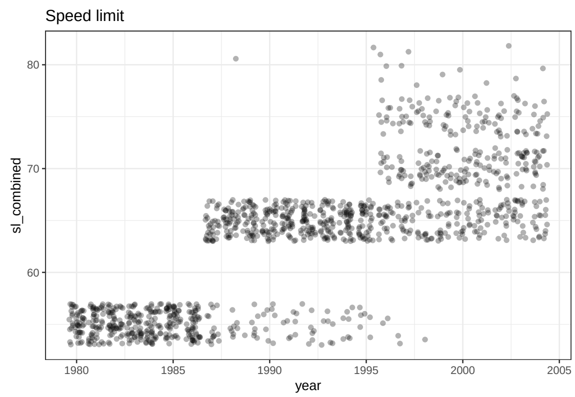
We noticed over time that fewer states have no BAC limit or 0.1 limit and more have a 0.08 limit.

```
ggplot(data, aes(x = as.factor(bac_combined), y = totfatrte)) +
    geom_boxplot() + ggtitle("BAC level vs Fatalities") + xlab("BAC level") +
    ylab("Fatalities per 100k population")
```



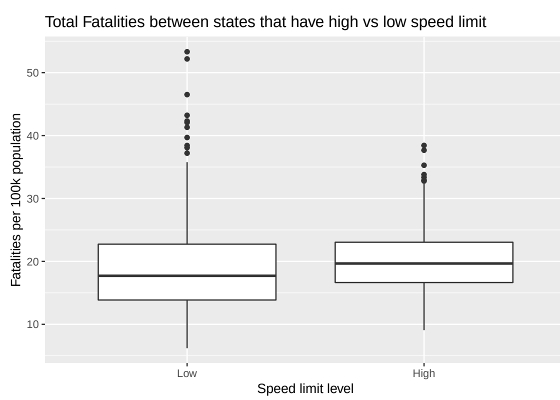
Fatalities appear to be lowest in states with a 0.08 BAC limit and highest in states with no BAC limit.

```
ggplot(data, aes(x = year, y = sl_combined, group = state)) +
    geom_jitter(alpha = 0.3) + theme_bw() + ggtitle("Speed limit")
```

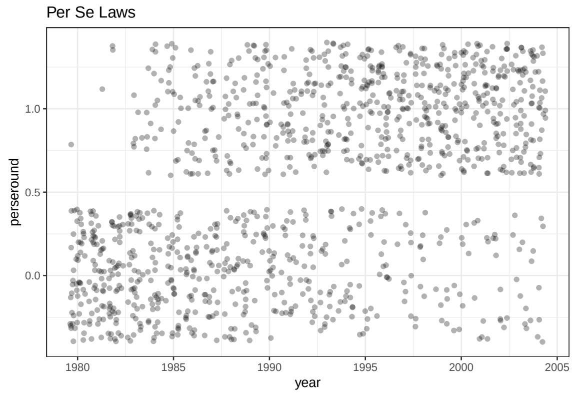


Over time, speed limits have increased.

```
data$slhigh <- (data$sl70plus == 1)
ggplot(data, aes(x = as.factor(slhigh), y = totfatrte)) + geom_boxplot() +
    ggtitle("Total Fatalities between states that have high vs low speed limit") +
    scale_x_discrete(labels = c("Low", "High")) + xlab("Speed limit level") +
    ylab("Fatalities per 100k population")
```

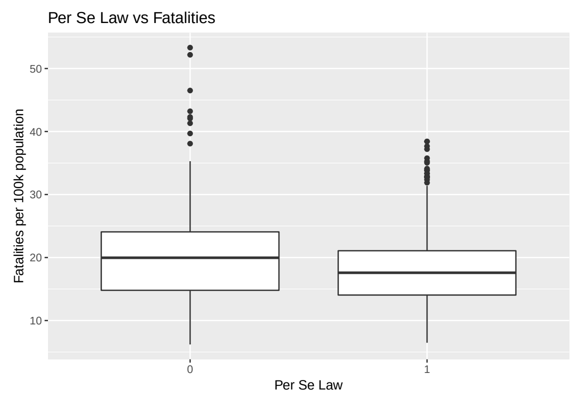



```
data$perseround = round(data$perse)
ggplot(data, aes(x = year, y = perseround, group = state)) +
    geom_jitter(alpha = 0.3) + theme_bw() + ggtitle("Per Se Laws")
```



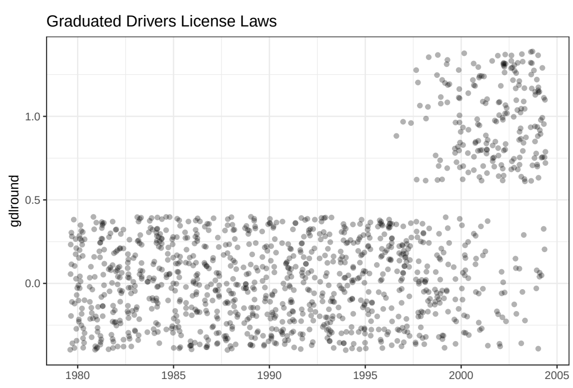
States have increasingly implemented per se laws over time.

```
ggplot(data, aes(x = as.factor(perseround), y = totfatrte)) +
    geom_boxplot() + ggtitle("Per Se Law vs Fatalities") + xlab("Per Se Law") +
    ylab("Fatalities per 100k population")
```



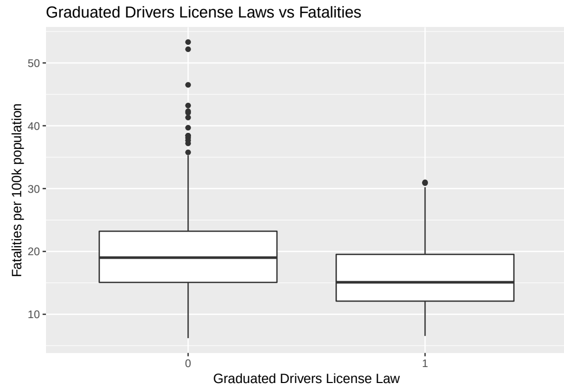
States with no per se laws have higher fatalities.

```
data$gdlround = round(data$gdl)
ggplot(data, aes(x = year, y = gdlround, group = state)) + geom_jitter(alpha = 0.3) +
    theme_bw() + ggtitle("Graduated Drivers License Laws")
```



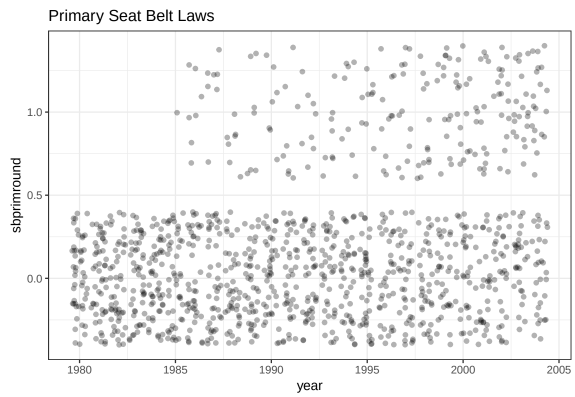
States have increasingly implemented graduated drivers license laws beginning in the late 90s.

```
ggplot(data, aes(x = as.factor(gdlround), y = totfatrte)) + geom_boxplot() +
    ggtitle("Graduated Drivers License Laws vs Fatalities") +
    xlab("Graduated Drivers License Law") + ylab("Fatalities per 100k population")
```



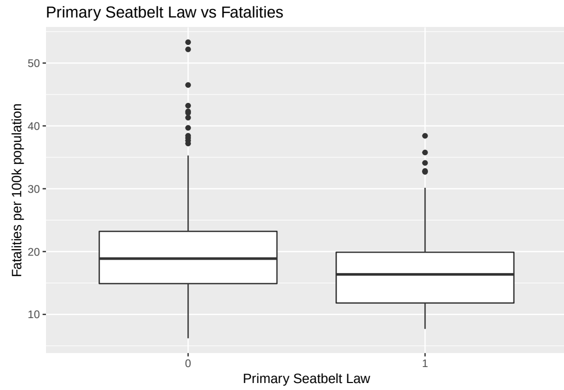
States with without graduated drivers license laws have higher fatalities.

```
data$sbprimround = round(data$sbprim)
ggplot(data, aes(x = year, y = sbprimround, group = state)) +
    geom_jitter(alpha = 0.3) + theme_bw() + ggtitle("Primary Seat Belt Laws")
```



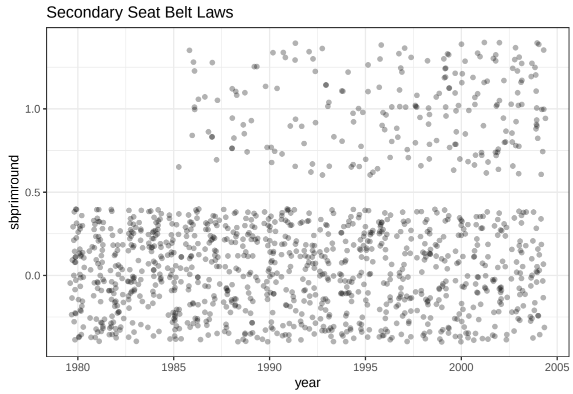
States have increasingly implemented primary seatbelt laws over time.

```
data$sbprimround = round(data$sbprim)
ggplot(data, aes(x = as.factor(sbprimround), y = totfatrte)) +
    geom_boxplot() + ggtitle("Primary Seatbelt Law vs Fatalities") +
    xlab("Primary Seatbelt Law") + ylab("Fatalities per 100k population")
```



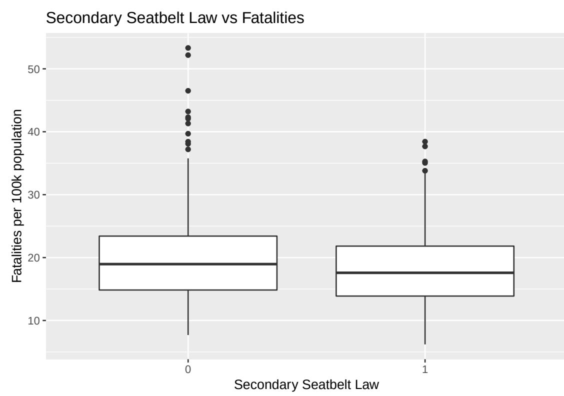
States with no primary seatbelt law have higher fatalities.

```
data$sbseconround = round(data$sbsecon)
ggplot(data, aes(x = year, y = sbprimround, group = state)) +
    geom_jitter(alpha = 0.3) + theme_bw() + ggtitle("Secondary Seat Belt Laws")
```



States have increasingly implemented secondary seatbelt laws over time.

```
data$sbseconround = round(data$sbsecon)
ggplot(data, aes(x = as.factor(sbseconround), y = totfatrte)) +
    geom_boxplot() + ggtitle("Secondary Seatbelt Law vs Fatalities") +
    xlab("Secondary Seatbelt Law") + ylab("Fatalities per 100k population")
```



States with no seconday seatbelt law have higher fatlities but the difference is less than the primary seatbelt laes.

2. How is the our dependent variable of interest *totfatrte* defined? What is the average of this variable in each of the years in the time period covered in this dataset? Estimate a linear regression model of *totfatrte* on a set of dummy variables for the years 1981 through 2004. What does this model explain? Describe what you find in this model. Did driving become safer over this period? Please provide a detailed explanation.

totfatrte is defined as "fatalities per 100,000 population"

```
# avg per year covered in data set
ddply(data, .(year), summarize, Total = mean(totfatrte))
```

```
##    year    Total
## 1  1980 25.49458
## 2  1981 23.67021
## 3  1982 20.94250
## 4  1983 20.15292
## 5  1984 20.26750
## 6  1985 19.85146
## 7  1986 20.80042
## 8  1987 20.77479
## 9  1988 20.89167
```

```
## 10 1989 19.77229
## 11 1990 19.50521
## 12 1991 18.09479
## 13 1992 17.15792
## 14 1993 17.12771
## 15 1994 17.15521
## 16 1995 17.66854
## 17 1996 17.36938
## 18 1997 17.61062
## 19 1998 17.26542
## 20 1999 17.25042
## 21 2000 16.82562
## 22 2001 16.79271
## 23 2002 17.02958
## 24 2003 16.76354
## 25 2004 16.72896
```

We'll estimate the linear regression model on the year dummies using the `totfatrte` column and the `year` column converted to a factor:

```r
# linear model
mod1 <- lm(totfatrte ~ factor(year), data = data)
summary(mod1)
```

```
##
## Call:
## lm(formula = totfatrte ~ factor(year), data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9302  -4.3468  -0.7305   3.7488  29.6498
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       25.4946     0.8671  29.401  < 2e-16 ***
## factor(year)1981  -1.8244     1.2263  -1.488 0.137094
## factor(year)1982  -4.5521     1.2263  -3.712 0.000215 ***
## factor(year)1983  -5.3417     1.2263  -4.356 1.44e-05 ***
## factor(year)1984  -5.2271     1.2263  -4.263 2.18e-05 ***
## factor(year)1985  -5.6431     1.2263  -4.602 4.64e-06 ***
## factor(year)1986  -4.6942     1.2263  -3.828 0.000136 ***
## factor(year)1987  -4.7198     1.2263  -3.849 0.000125 ***
## factor(year)1988  -4.6029     1.2263  -3.754 0.000183 ***
## factor(year)1989  -5.7223     1.2263  -4.666 3.42e-06 ***
## factor(year)1990  -5.9894     1.2263  -4.884 1.18e-06 ***
## factor(year)1991  -7.3998     1.2263  -6.034 2.14e-09 ***
## factor(year)1992  -8.3367     1.2263  -6.798 1.68e-11 ***
## factor(year)1993  -8.3669     1.2263  -6.823 1.43e-11 ***
## factor(year)1994  -8.3394     1.2263  -6.800 1.66e-11 ***
## factor(year)1995  -7.8260     1.2263  -6.382 2.51e-10 ***
## factor(year)1996  -8.1252     1.2263  -6.626 5.25e-11 ***
## factor(year)1997  -7.8840     1.2263  -6.429 1.86e-10 ***
## factor(year)1998  -8.2292     1.2263  -6.711 3.01e-11 ***
## factor(year)1999  -8.2442     1.2263  -6.723 2.77e-11 ***
## factor(year)2000  -8.6690     1.2263  -7.069 2.67e-12 ***
```

```
## factor(year)2001  -8.7019     1.2263  -7.096 2.21e-12 ***
## factor(year)2002  -8.4650     1.2263  -6.903 8.32e-12 ***
## factor(year)2003  -8.7310     1.2263  -7.120 1.88e-12 ***
## factor(year)2004  -8.7656     1.2263  -7.148 1.54e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.008 on 1175 degrees of freedom
## Multiple R-squared:  0.1276, Adjusted R-squared:  0.1098
## F-statistic: 7.164 on 24 and 1175 DF,  p-value: < 2.2e-16
```

The summary shows that the coefficients are estimated to be negative for each year after 1980, with the coefficients being statistically significant for all years except 1981. This corroborates the observations we made in the box plot of `totfatrte` over time. Does this mean that driving became safer over this time period? The answer to that question is multi-faceted - better driving habits, more/less speeding, frequency of drunk driving, car safety. need to elaborate and reword this portion.

3. Expand your model in *Exercise 2* by adding variables *bac08, bac10, perse, sbprim, sbsecon, sl70plus, gdl, perc14_24, unem, vehicmilespc*, and perhaps *transformations of some or all of these variables.* Please explain carefully your rationale, which should be based on your EDA, behind any transformation you made. If no transformation is made, explain why transformation is not needed. How are the variables *bac8* and *bac10* defined? Interpret the coefficients on *bac8* and *bac10.* Do *per se laws* have a negative effect on the fatality rate? What about having a primary seat belt law? (Note that if a law was enacted sometime within a year the fraction of the year is recorded in place of the zero-one indicator.)

I think we should log transform unem Should we include a latex rendering of the model we'll estimate? We may score extra points by doing that... yesssss we def should

```r
data$bac08round = round(data$bac08)
data$bac10round = round(data$bac10)
data$sl70plusround = round(data$sl70plus)

mod2 <- lm(totfatrte ~ factor(year) + bac08round + bac10round +
    perseround + sbprimround + sbseconround + sl70plusround +
    gdlround + perc14_24 + log(unem) + vehicmilespc, data = data)

summary(mod2)
```

```
##
## Call:
## lm(formula = totfatrte ~ factor(year) + bac08round + bac10round +
##     perseround + sbprimround + sbseconround + sl70plusround +
##     gdlround + perc14_24 + log(unem) + vehicmilespc, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.4031  -2.6086  -0.3265   2.2414  21.8650
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -8.012e+00  2.620e+00  -3.058 0.002277 **
## factor(year)1981 -2.107e+00  8.229e-01  -2.560 0.010578 *
## factor(year)1982 -6.304e+00  8.397e-01  -7.508 1.19e-13 ***
## factor(year)1983 -7.190e+00  8.515e-01  -8.445  < 2e-16 ***
## factor(year)1984 -5.826e+00  8.666e-01  -6.723 2.78e-11 ***
## factor(year)1985 -6.458e+00  8.852e-01  -7.296 5.48e-13 ***
```

```
## factor(year)1986 -5.634e+00  9.231e-01  -6.103 1.42e-09 ***
## factor(year)1987 -6.065e+00  9.613e-01  -6.309 3.98e-10 ***
## factor(year)1988 -6.176e+00  1.011e+00  -6.109 1.36e-09 ***
## factor(year)1989 -7.688e+00  1.049e+00  -7.325 4.43e-13 ***
## factor(year)1990 -8.682e+00  1.072e+00  -8.102 1.36e-15 ***
## factor(year)1991 -1.087e+01  1.093e+00  -9.944  < 2e-16 ***
## factor(year)1992 -1.263e+01  1.114e+00 -11.335  < 2e-16 ***
## factor(year)1993 -1.250e+01  1.128e+00 -11.085  < 2e-16 ***
## factor(year)1994 -1.208e+01  1.150e+00 -10.500  < 2e-16 ***
## factor(year)1995 -1.147e+01  1.180e+00  -9.722  < 2e-16 ***
## factor(year)1996 -1.340e+01  1.223e+00 -10.962  < 2e-16 ***
## factor(year)1997 -1.352e+01  1.244e+00 -10.864  < 2e-16 ***
## factor(year)1998 -1.420e+01  1.268e+00 -11.197  < 2e-16 ***
## factor(year)1999 -1.415e+01  1.284e+00 -11.019  < 2e-16 ***
## factor(year)2000 -1.440e+01  1.307e+00 -11.021  < 2e-16 ***
## factor(year)2001 -1.567e+01  1.317e+00 -11.903  < 2e-16 ***
## factor(year)2002 -1.649e+01  1.326e+00 -12.434  < 2e-16 ***
## factor(year)2003 -1.692e+01  1.331e+00 -12.716  < 2e-16 ***
## factor(year)2004 -1.633e+01  1.367e+00 -11.947  < 2e-16 ***
## bac08round       -2.288e+00  4.858e-01  -4.709 2.79e-06 ***
## bac10round       -1.256e+00  3.591e-01  -3.497 0.000489 ***
## perseround       -5.625e-01  2.919e-01  -1.927 0.054231 .
## sbprimround      -3.795e-01  4.898e-01  -0.775 0.438515
## sbseconround     -1.535e-01  4.279e-01  -0.359 0.719911
## sl70plusround     3.112e+00  4.331e-01   7.186 1.19e-12 ***
## gdlround         -3.014e-01  5.066e-01  -0.595 0.552051
## perc14_24         1.776e-01  1.222e-01   1.453 0.146542
## log(unem)         5.152e+00  4.812e-01  10.707  < 2e-16 ***
## vehicmilespc      2.921e-03  9.393e-05  31.096  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.024 on 1165 degrees of freedom
## Multiple R-squared:  0.6119, Adjusted R-squared:  0.6006
## F-statistic: 54.02 on 34 and 1165 DF,  p-value: < 2.2e-16
```

bac8 is blood alcohol limit .08 bac10 is blood alcohol limit .10

This model indicates that in addition to years, blood alcohol limis of either .08 or .1 have a significant impact decreasing fatalities in car accidents. Further, it indicates that speed limits over 70, high unemployment, and high vehicle miles per capita have significant impact increasing fatalities from car accidents.

4. Reestimate the model from *Exercise 3* using a fixed effects (at the state level) model. How do the coefficients on *bac08, bac10, perse, and sbprim* compare with the pooled OLS estimates? Which set of estimates do you think is more reliable? What assumptions are needed in each of these models? Are these assumptions reasonable in the current context?

```r
data$bac08round <- round(data$bac08)
data$bac10round <- round(data$bac10)
data$sl70plusround <- round(data$sl70plus)
data$perseround <- round(data$perse)
data$sbprimround <- round(data$sbprim)
data$sbseconround = round(data$sbsecon)
data$gdlround = round(data$gdl)

model.fe <- plm(totfatrte ~ factor(year) + bac08round + bac10round +
```

```r
    perseround + sbprimround + sbseconround + sl70plusround +
    gdlround + perc14_24 + log(unem) + vehicmilespc, data = data,
    index = c("state", "year"), model = "within")

summary(model.fe)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = totfatrte ~ factor(year) + bac08round + bac10round +
##     perseround + sbprimround + sbseconround + sl70plusround +
##     gdlround + perc14_24 + log(unem) + vehicmilespc, data = data,
##     model = "within", index = c("state", "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##     Min.  1st Qu.   Median  3rd Qu.     Max.
## -8.24190 -1.03559 -0.01383  0.97540 14.63249
##
## Coefficients:
##                     Estimate  Std. Error  t-value  Pr(>|t|)
## factor(year)1981 -1.5789e+00  4.1364e-01  -3.8171 0.0001424 ***
## factor(year)1982 -3.3715e+00  4.3392e-01  -7.7699 1.771e-14 ***
## factor(year)1983 -4.0253e+00  4.4540e-01  -9.0376 < 2.2e-16 ***
## factor(year)1984 -4.5466e+00  4.5989e-01  -9.8863 < 2.2e-16 ***
## factor(year)1985 -4.9961e+00  4.8064e-01 -10.3947 < 2.2e-16 ***
## factor(year)1986 -3.9860e+00  5.1473e-01  -7.7438 2.152e-14 ***
## factor(year)1987 -4.6704e+00  5.5481e-01  -8.4180 < 2.2e-16 ***
## factor(year)1988 -5.2103e+00  6.0465e-01  -8.6170 < 2.2e-16 ***
## factor(year)1989 -6.5240e+00  6.4330e-01 -10.1416 < 2.2e-16 ***
## factor(year)1990 -6.5808e+00  6.6583e-01  -9.8835 < 2.2e-16 ***
## factor(year)1991 -7.2511e+00  6.8047e-01 -10.6560 < 2.2e-16 ***
## factor(year)1992 -8.1283e+00  7.0115e-01 -11.5928 < 2.2e-16 ***
## factor(year)1993 -8.4679e+00  7.1473e-01 -11.8476 < 2.2e-16 ***
## factor(year)1994 -8.9443e+00  7.3383e-01 -12.1885 < 2.2e-16 ***
## factor(year)1995 -8.7095e+00  7.5904e-01 -11.4743 < 2.2e-16 ***
## factor(year)1996 -9.1278e+00  8.0059e-01 -11.4013 < 2.2e-16 ***
## factor(year)1997 -9.3884e+00  8.2150e-01 -11.4283 < 2.2e-16 ***
## factor(year)1998 -1.0104e+01  8.4200e-01 -11.9999 < 2.2e-16 ***
## factor(year)1999 -1.0347e+01  8.5217e-01 -12.1422 < 2.2e-16 ***
## factor(year)2000 -1.0957e+01  8.6601e-01 -12.6518 < 2.2e-16 ***
## factor(year)2001 -1.0458e+01  8.6660e-01 -12.0674 < 2.2e-16 ***
## factor(year)2002 -9.6024e+00  8.6989e-01 -11.0387 < 2.2e-16 ***
## factor(year)2003 -9.6414e+00  8.7258e-01 -11.0493 < 2.2e-16 ***
## factor(year)2004 -1.0076e+01  8.9852e-01 -11.2135 < 2.2e-16 ***
## bac08round       -1.1048e+00  3.3064e-01  -3.3413 0.0008616 ***
## bac10round       -8.0362e-01  2.2577e-01  -3.5594 0.0003873 ***
## perseround       -1.1270e+00  2.2337e-01  -5.0456 5.273e-07 ***
## sbprimround      -1.1891e+00  3.4319e-01  -3.4649 0.0005505 ***
## sbseconround     -3.0375e-01  2.5224e-01  -1.2042 0.2287712
## sl70plusround     4.7115e-02  2.6094e-01   0.1806 0.8567466
## gdlround         -2.8250e-01  2.8028e-01  -1.0079 0.3137115
## perc14_24         1.6728e-01  9.5431e-02   1.7529 0.0798887 .
```

```
## log(unem)        -3.7089e+00  3.9240e-01  -9.4519 < 2.2e-16 ***
## vehicmilespc      9.5062e-04  1.1018e-04   8.6281 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    12134
## Residual Sum of Squares: 4552.4
## R-Squared:      0.62483
## Adj. R-Squared: 0.59765
## F-statistic: 54.7637 on 34 and 1118 DF, p-value: < 2.22e-16
```

5. Would you perfer to use a random effects model instead of the fixed effects model you built in *Exercise 4*? Please explain.

To determine whether random effects model should be used over the fixed effects model, we can conducts a Hausman test with the null hypothesis that the preferred model is random effects.

```
model.re <- plm(totfatrte ~ factor(year) + bac08round + bac10round +
    perseround + sbprimround + sbseconround + sl70plusround +
    gdlround + perc14_24 + log(unem) + vehicmilespc, data = data,
    index = c("state", "year"), model = "random")
phtest(model.fe, model.re)
```

```
##
##  Hausman Test
##
## data:  totfatrte ~ factor(year) + bac08round + bac10round + perseround +  ...
## chisq = 180.54, df = 34, p-value < 2.2e-16
## alternative hypothesis: one model is inconsistent
```

With the p-value < 2.2e-16, we can reject the null hypothesis that the random effects assumptions are correct and we would prefer to use the fixed effects model.

6. Suppose that *vehicmilespc*, the number of miles driven per capita, increases by $1,000$. Using the FE estimates, what is the estimated effect on *totfatrte*? Please interpret the estimate.

According to our fixed effect model, the coefficient for *vehicmilespc* variable was 0.000951 fatalities/100k people per mile driven per capita. For all other things held equal, if, on average, there's an increase of 1,000 miles driven per capita, we would expect an increase of 0.951 (approximately 1) fatalities per 100k people.

7. If there is serial correlation or heteroskedasticity in the idiosyncratic errors of the model, what would be the consequences on the estimators and their standard errors?

The fixed effects model assumes that the idiosyncratic errors are uncorrelated. If there is serial correlation in the model errors, the estimated variance will be biased which will result in underestimated standard errors and thus rending most statistical tests invalid. This would most likely commit Type I error, and reject the null hypothesis too easily.

Heteroskedasticity in the idiosyncratic errors would result in overstated standard errors and may commit Type II error. We may fail to reject the null hypothesis since significance of potentially valuable regressor will not be detected.