Statistical Methods for Discrete Response, Time Series, and Panel Data (W271): Group Lab 3

Due Sunday 8 August 2021 11:59pm

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Instructions (Please Read Carefully):

- Submit by the due date. **Late submissions will not be accepted**
- 20 page limit (strict)
- Do not modify fontsize, margin or line-spacing settings
- One student from each group should submit the lab to their student github repo by the deadline
- Submit two files:

  1. A pdf file that details your answers. Include all R code used to produce the answers
  2. The R markdown (Rmd) file used to produce the pdf file

  The assignment will not be graded unless **both** files are submitted
- Name your files to include all group members' names. For example, if the students' names are Stan Cartman and Kenny Kyle, name your files as follows:

  - `StanCartman_KennyKyle_Lab3.Rmd`
  - `StanCartman_KennyKyle_Lab3.pdf`
- Although it sounds obvious, please write your name on page 1 of your pdf and Rmd files
- All answers should include a detailed narrative; make sure that your audience can easily follow the logic of your analysis. All steps used in modelling must be clearly shown and explained; do not simply 'output dump' the results of code without explanation
- If you use libraries and functions for statistical modeling that we have not covered in this course, you must provide an explanation of why such libraries and functions are used and reference the library documentation
- For mathematical formulae, type them in your R markdown file. Do not e.g. write them on a piece of paper, snap a photo, and use the image file
- Incorrectly following submission instructions results in deduction of grades
- Students are expected to act with regard to UC Berkeley Academic Integrity.

U.S. traffic fatalities: 1980-2004

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 economic and demographic variables are also included. The description of the each of the variables in the dataset is come with the dataset.

1. (30%) 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.*

Response to Q1: The EDA below displays many different graphs and tables of the data. The first table if the correlation plot of all the variables. The dependent variable of interest is the totfatrte, which is the total fatality rate of driving incidents. From the correlation plot, the variables that seem to best correlate with this variable are, the year, seatbelt, minage, gdl, zerotol, vehiclemiles. All these variables are negatively correlated with the dependent variable. There are some variables that are strongly correlated with the dependent variable in a positive way and these include unem, perc14_24, and vehicmilespc. Since some of the speedlimit correlated go from being positive and negative, it seems that the data is inconclusive here on how changing the speed limit may affect driving incidents. Also, it is important to note that all the other measurements of fatality are highly correlated with the dependent variable, however these variables are not independent of one another and are essentially part of the same thing, therefore we will not use them in the model.

It is also important to note that there is no missing data from the data, and the data goes from 1980 through 2004 and includes 48 different states. The data is set up to have all the data in the time frame of 1980 to 2004 for each state, therefore we can see the changes over time for each individual state and model all the changes together in one model. Only the variables from the data that were discussed above for having a strong correlation to the dependent variable will be analyzed from here on out.

Since the year was negatively correlated I was interested to model the change in totfatrte over time. All the states were modeled on plots, however for sake of conducting a concise analysis only one plot of 12 different states is shown below. This plot shows the different states over time. We are not necessarily interested on how an individual model's data looks, but rather the overall change, and overall the data looks like it does slightly decrease over the 25 year span. The other data plots that are not shown showed similar plots.

Lastly, the histograms of all the variable in consideration for the model are shown below. It is difficult to assess what some of the histograms mean, since we do not have information on what

some of these variable acronyms mean. However, the point of plotting the histograms of these variables is to see any extreme distribution in the data. Most of the data is generally normal, mainly a lot of the data has right sided tails which may lead to a transformation of that variable in order to obtain a more normal distribution, however these transformations will be discussed in the model formulation part of the lab.

```
library(plm)
library(funModeling)
library(tidyverse)
library(Hmisc)
library(ggplot2)
library(forecast)
library(tseries)
library(corrr)
```

```
#load("driving.RData", ex <- new.env())
#ls.str(ex)
load("driving.RData")
head(data,5)
```

```
##   year state sl55 sl65 sl70 sl75 slnone seatbelt minage zerotol gdl bac10 bac08
## 1 1980     1    1    0    0    0      0        0     18       0   0     1     0
## 2 1981     1    1    0    0    0      0        0     18       0   0     1     0
## 3 1982     1    1    0    0    0      0        0     18       0   0     1     0
## 4 1983     1    1    0    0    0      0        0     18       0   0     1     0
## 5 1984     1    1    0    0    0      0        0     18       0   0     1     0
##   perse totfat nghtfat wkndfat totfatpvm nghtfatpvm wkndfatpvm statepop
## 1     0    940     422     236      3.20      1.437      0.803  3893888
## 2     0    933     434     248      3.35      1.558      0.890  3918520
## 3     0    839     376     224      2.81      1.259      0.750  3925218
## 4     0    930     397     223      3.00      1.281      0.719  3934109
## 5     0    932     421     237      2.83      1.278      0.720  3951834
##   totfatrte nghtfatrte wkndfatrte vehicmiles unem perc14_24 sl70plus sbprim
## 1     24.14      10.84       6.06   29.37500  8.8      18.9        0      0
## 2     24.07      11.08       6.33   27.85200 10.7      18.7        0      0
## 3     21.37       9.58       5.71   29.85765 14.4      18.4        0      0
## 4     23.64      10.09       5.67   31.00000 13.7      18.0        0      0
## 5     23.58      10.65       6.00   32.93286 11.1      17.6        0      0
##   sbsecon d80 d81 d82 d83 d84 d85 d86 d87 d88 d89 d90 d91 d92 d93 d94 d95 d96
## 1       0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## 2       0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## 3       0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## 4       0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0
## 5       0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0
##   d97 d98 d99 d00 d01 d02 d03 d04 vehicmilespc
## 1   0   0   0   0   0   0   0   0     7543.874
## 2   0   0   0   0   0   0   0   0     7107.785
```

```
## 3   0   0   0   0   0   0   0   0     7606.622
## 4   0   0   0   0   0   0   0   0     7879.802
## 5   0   0   0   0   0   0   0   0     8333.562
```

```
df <- pdata.frame(data, index=c("state", 'year'))
#head(df, 20)
```

```
correlate(data)
```

```
##
## Correlation method: 'pearson'
## Missing treated using: 'pairwise.complete.obs'
```

```
## # A tibble: 56 x 57
##    term         year     state    sl55    sl65    sl70    sl75   slnone seatbelt
##    <chr>       <dbl>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>    <dbl>    <dbl>
##  1 year    NA        -4.46e-22 -0.778   0.269   0.427   0.336   9.67e-2   0.649
##  2 state   -4.46e-22 NA        -0.0192  0.0375 -0.0746  0.0548 -8.89e-4   0.0264
##  3 sl55    -7.78e- 1 -1.92e- 2 NA      -0.649  -0.280  -0.224  -6.60e-2  -0.639
##  4 sl65     2.69e- 1  3.75e- 2 -0.649  NA      -0.321  -0.261  -7.82e-2   0.339
##  5 sl70     4.27e- 1 -7.46e- 2 -0.280  -0.321  NA      -0.109  -3.27e-2   0.203
##  6 sl75     3.36e- 1  5.48e- 2 -0.224  -0.261  -0.109  NA      -2.62e-2   0.236
##  7 slnone   9.67e- 2 -8.89e- 4 -0.0660 -0.0782 -0.0327 -0.0262 NA         0.0863
##  8 seatbe~  6.49e- 1  2.64e- 2 -0.639   0.339   0.203   0.236   8.63e-2  NA
##  9 minage   5.71e- 1 -1.66e- 2 -0.579   0.376   0.162   0.129   3.81e-2   0.509
## 10 zerotol  7.89e- 1  2.76e- 2 -0.570   0.124   0.400   0.279   5.74e-2   0.456
## # ... with 46 more rows, and 48 more variables: minage <dbl>, zerotol <dbl>,
## #   gdl <dbl>, bac10 <dbl>, bac08 <dbl>, perse <dbl>, totfat <dbl>,
## #   nghtfat <dbl>, wkndfat <dbl>, totfatpvm <dbl>, nghtfatpvm <dbl>,
## #   wkndfatpvm <dbl>, statepop <dbl>, totfatrte <dbl>, nghtfatrte <dbl>,
## #   wkndfatrte <dbl>, vehicmiles <dbl>, unem <dbl>, perc14_24 <dbl>,
## #   sl70plus <dbl>, sbprim <dbl>, sbsecon <dbl>, d80 <dbl>, d81 <dbl>,
## #   d82 <dbl>, d83 <dbl>, d84 <dbl>, d85 <dbl>, d86 <dbl>, d87 <dbl>,
## #   d88 <dbl>, d89 <dbl>, d90 <dbl>, d91 <dbl>, d92 <dbl>, d93 <dbl>,
## #   d94 <dbl>, d95 <dbl>, d96 <dbl>, d97 <dbl>, d98 <dbl>, d99 <dbl>,
## #   d00 <dbl>, d01 <dbl>, d02 <dbl>, d03 <dbl>, d04 <dbl>, vehicmilespc <dbl>
```

```
sum(is.na(data))
```

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

```
summary(data)
```

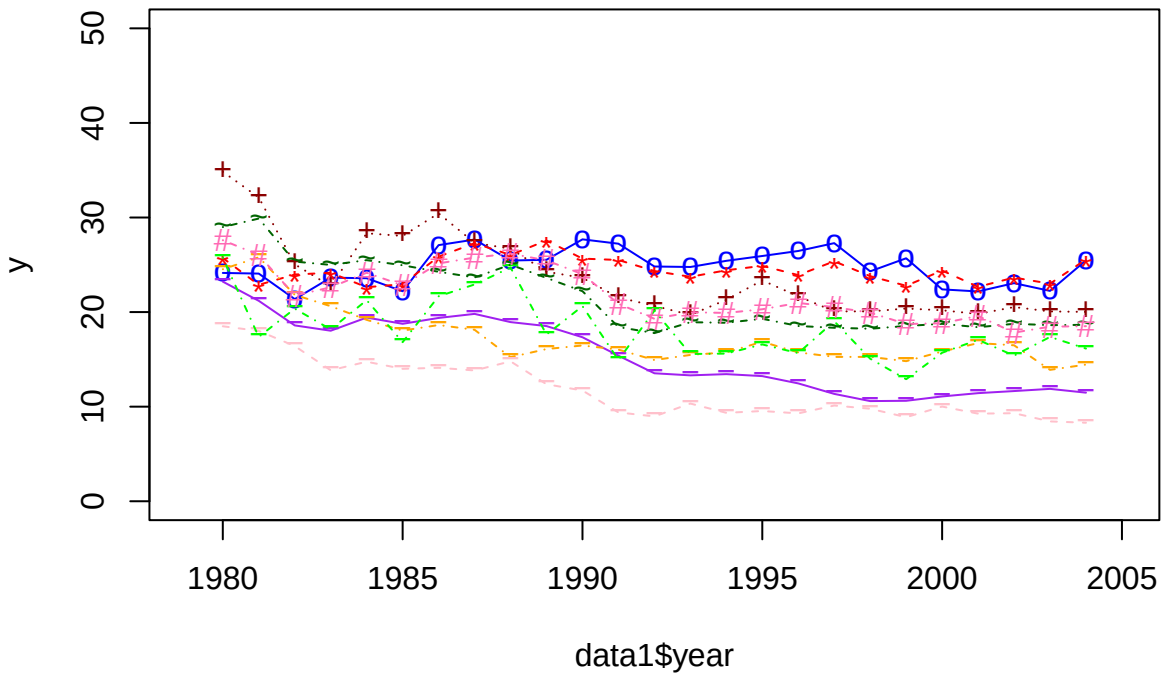
```
##       year          state            sl55             sl65
##  Min.   :1980   Min.   : 1.00   Min.   :0.0000   Min.   :0.0000
```

```
##  1st Qu.:1986   1st Qu.:15.75   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1992   Median :27.50   Median :0.0000   Median :0.0000
##  Mean   :1992   Mean   :27.15   Mean   :0.3533   Mean   :0.4399
##  3rd Qu.:1998   3rd Qu.:39.25   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :2004   Max.   :51.00   Max.   :1.0000   Max.   :1.0000
##       sl70            sl75             slnone           seatbelt
##  Min.   :0.000   Min.   :0.00000   Min.   :0.000000   Min.   :0.000
##  1st Qu.:0.000   1st Qu.:0.00000   1st Qu.:0.000000   1st Qu.:0.000
##  Median :0.000   Median :0.00000   Median :0.000000   Median :1.000
##  Mean   :0.119   Mean   :0.08024   Mean   :0.007569   Mean   :1.116
##  3rd Qu.:0.000   3rd Qu.:0.00000   3rd Qu.:0.000000   3rd Qu.:2.000
##  Max.   :1.000   Max.   :1.00000   Max.   :1.000000   Max.   :2.000
##      minage        zerotol            gdl              bac10
##  Min.   :18.0   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:21.0   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :21.0   Median :0.0000   Median :0.0000   Median :1.0000
##  Mean   :20.6   Mean   :0.4519   Mean   :0.1741   Mean   :0.6231
##  3rd Qu.:21.0   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :21.0   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##      bac08            perse           totfat          nghtfat
##  Min.   :0.0000   Min.   :0.0000   Min.   :  63.0   Min.   :  26.0
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.: 310.0   1st Qu.: 139.8
##  Median :0.0000   Median :1.0000   Median : 676.0   Median : 316.0
##  Mean   :0.2135   Mean   :0.5471   Mean   : 900.7   Mean   : 427.3
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1099.5   3rd Qu.: 518.2
##  Max.   :1.0000   Max.   :1.0000   Max.   :5504.0   Max.   :2918.0
##     wkndfat         totfatpvm       nghtfatpvm       wkndfatpvm
##  Min.   :  10.0   Min.   :0.780   Min.   :0.2700   Min.   :0.1140
##  1st Qu.:  70.0   1st Qu.:1.577   1st Qu.:0.6847   1st Qu.:0.3410
##  Median : 163.0   Median :2.020   Median :0.9130   Median :0.4770
##  Mean   : 222.3   Mean   :2.122   Mean   :0.9990   Mean   :0.5255
##  3rd Qu.: 277.0   3rd Qu.:2.500   3rd Qu.:1.2110   3rd Qu.:0.6420
##  Max.   :1499.0   Max.   :5.700   Max.   :3.0030   Max.   :1.6750
##     statepop          totfatrte       nghtfatrte       wkndfatrte
##  Min.   :  453401   Min.   : 6.20   Min.   : 2.660   Min.   : 1.180
##  1st Qu.: 1641938   1st Qu.:14.38   1st Qu.: 6.338   1st Qu.: 3.240
##  Median : 3700425   Median :18.43   Median : 8.420   Median : 4.390
##  Mean   : 5329896   Mean   :18.92   Mean   : 8.796   Mean   : 4.606
##  3rd Qu.: 6069563   3rd Qu.:22.77   3rd Qu.:10.650   3rd Qu.: 5.680
##  Max.   :35894000   Max.   :53.32   Max.   :29.600   Max.   :14.430
##    vehicmiles           unem          perc14_24        sl70plus
##  Min.   :  3.703   Min.   : 2.200   Min.   :11.70   Min.   :0.0000
##  1st Qu.: 14.574   1st Qu.: 4.500   1st Qu.:13.90   1st Qu.:0.0000
##  Median : 33.863   Median : 5.600   Median :14.90   Median :0.0000
##  Mean   : 46.323   Mean   : 5.951   Mean   :15.33   Mean   :0.2068
##  3rd Qu.: 58.639   3rd Qu.: 7.000   3rd Qu.:16.60   3rd Qu.:0.0000
##  Max.   :329.600   Max.   :18.000   Max.   :20.30   Max.   :1.0000
##      sbprim          sbsecon            d80             d81            d82
```

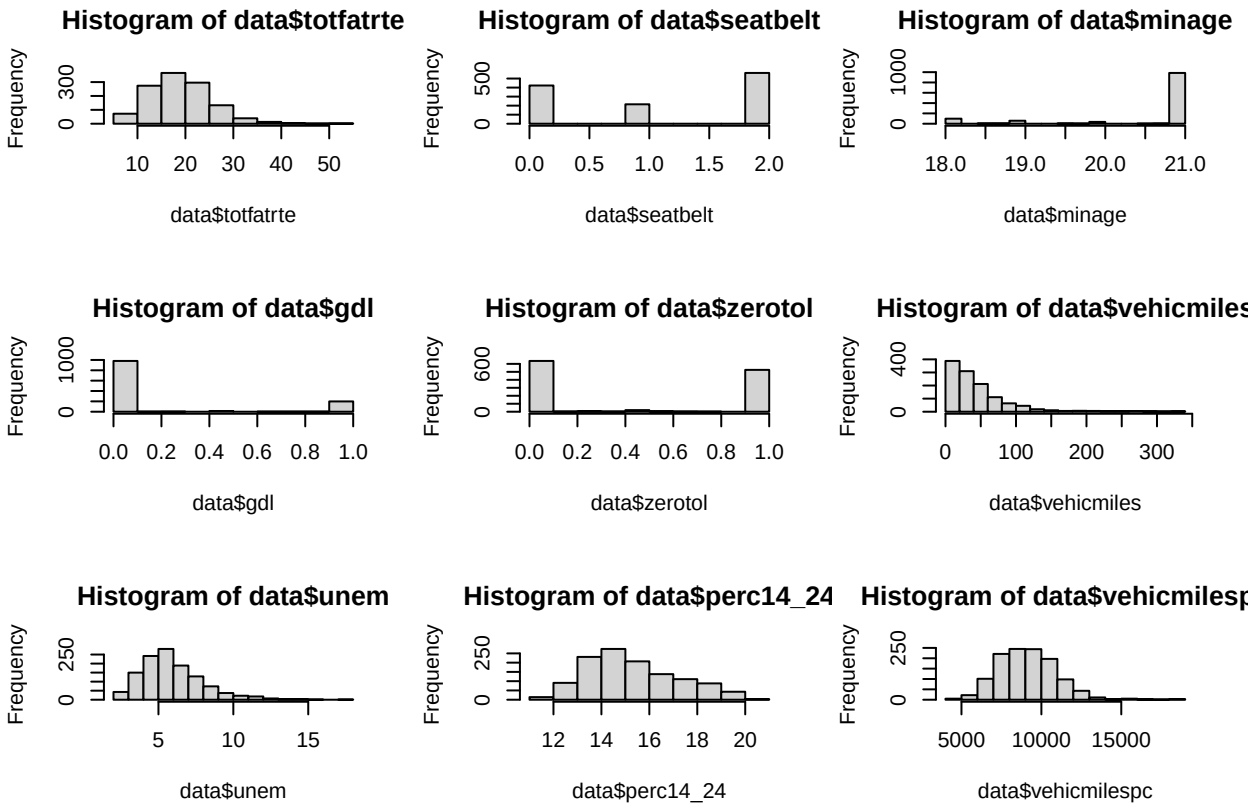
```
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.00   Min.   :0.00   Min.   :0.00
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00
##  Median :0.0000   Median :0.0000   Median :0.00   Median :0.00   Median :0.00
##  Mean   :0.1792   Mean   :0.4683   Mean   :0.04   Mean   :0.04   Mean   :0.04
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.00   Max.   :1.00   Max.   :1.00
##       d83              d84              d85              d86              d87
##  Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00
##  1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00
##  Median :0.00   Median :0.00   Median :0.00   Median :0.00   Median :0.00
##  Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04
##  3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00
##  Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00
##       d88              d89              d90              d91              d92
##  Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00
##  1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00
##  Median :0.00   Median :0.00   Median :0.00   Median :0.00   Median :0.00
##  Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04
##  3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00
##  Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00
##       d93              d94              d95              d96              d97
##  Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00
##  1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00
##  Median :0.00   Median :0.00   Median :0.00   Median :0.00   Median :0.00
##  Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04
##  3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00
##  Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00
##       d98              d99              d00              d01              d02
##  Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.00
##  1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00
##  Median :0.00   Median :0.00   Median :0.00   Median :0.00   Median :0.00
##  Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04   Mean   :0.04
##  3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:0.00
##  Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.00
##       d03              d04        vehicmilespc
##  Min.   :0.00   Min.   :0.00   Min.   : 4372
##  1st Qu.:0.00   1st Qu.:0.00   1st Qu.: 7788
##  Median :0.00   Median :0.00   Median : 9013
##  Mean   :0.04   Mean   :0.04   Mean   : 9129
##  3rd Qu.:0.00   3rd Qu.:0.00   3rd Qu.:10327
##  Max.   :1.00   Max.   :1.00   Max.   :18390
```

```r
data1 <- subset(data, state == 1)
data2 <- subset(data, state == 2)
data3 <- subset(data, state == 3)
data4 <- subset(data, state == 4)
data5 <- subset(data, state == 5)
```

```
data6 <- subset(data, state == 6)
data7 <- subset(data, state == 7)
data8 <- subset(data, state == 8)
data9 <- subset(data, state == 9)
data10 <- subset(data, state == 10)
data11 <- subset(data, state == 11)
data12 <- subset(data, state == 12)

#plot the first data series using plot()
plot(data1$year, data1$totfatrte, type="o", col="blue", pch="o", ylab="y", lty=1, ylim=c(0,50)

#add third data series to the same chart using points() and lines()
points(data3$year, data3$totfatrte, col="dark red",pch="+")
lines(data3$year, data3$totfatrte, col="dark red", lty=3)

points(data4$year, data4$totfatrte, col="red", pch="*")
lines(data4$year, data4$totfatrte, col="red",lty=2)

points(data5$year, data5$totfatrte, col="purple", pch="-")
lines(data5$year, data5$totfatrte, col="purple",lty=1)

points(data6$year, data6$totfatrte, col="orange", pch="-")
lines(data6$year, data6$totfatrte, col="orange",lty=4)

points(data7$year, data7$totfatrte, col="pink", pch="-")
lines(data7$year, data7$totfatrte, col="pink",lty=2)

points(data8$year, data8$totfatrte, col="green", pch="-")
lines(data8$year, data8$totfatrte, col="green",lty=4)

points(data9$year, data9$totfatrte, col="dark blue", pch="-")
lines(data9$year, data9$totfatrte, col="dark blue",lty=4)

points(data10$year, data10$totfatrte, col="dark green", pch="~")
lines(data10$year, data10$totfatrte, col="dark green",lty=4)

points(data11$year, data11$totfatrte, col="hot pink", pch="#")
lines(data11$year, data11$totfatrte, col="hot pink",lty=4)

points(data12$year, data12$totfatrte, col="sea green", pch="+")
lines(data12$year, data12$totfatrte, col="sea green",lty=4)
```

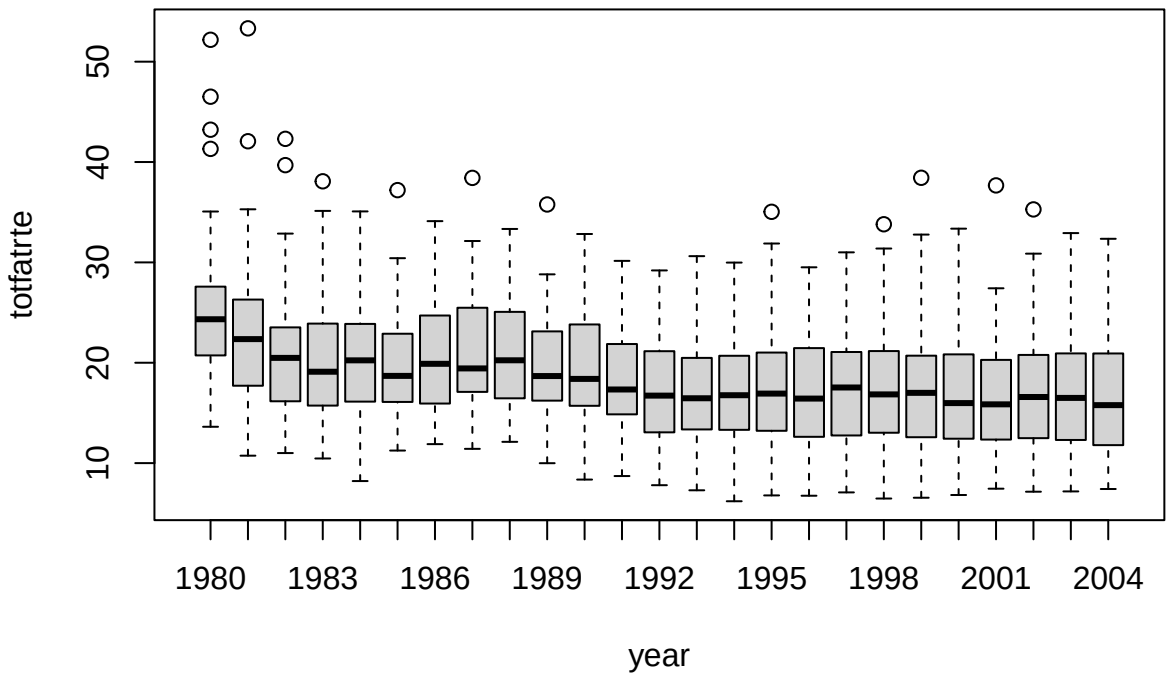



```
par(mfrow=c(3,3))
hist(data$totfatrte)
hist(data$seatbelt)
hist(data$minage)
hist(data$gdl)
hist(data$zerotol)
hist(data$vehicmiles)
hist(data$unem)
hist(data$perc14_24)
hist(data$vehicmilespc)
```



2. (15%) 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.

```
boxplot(totfatrte ~ year, data=data)
```

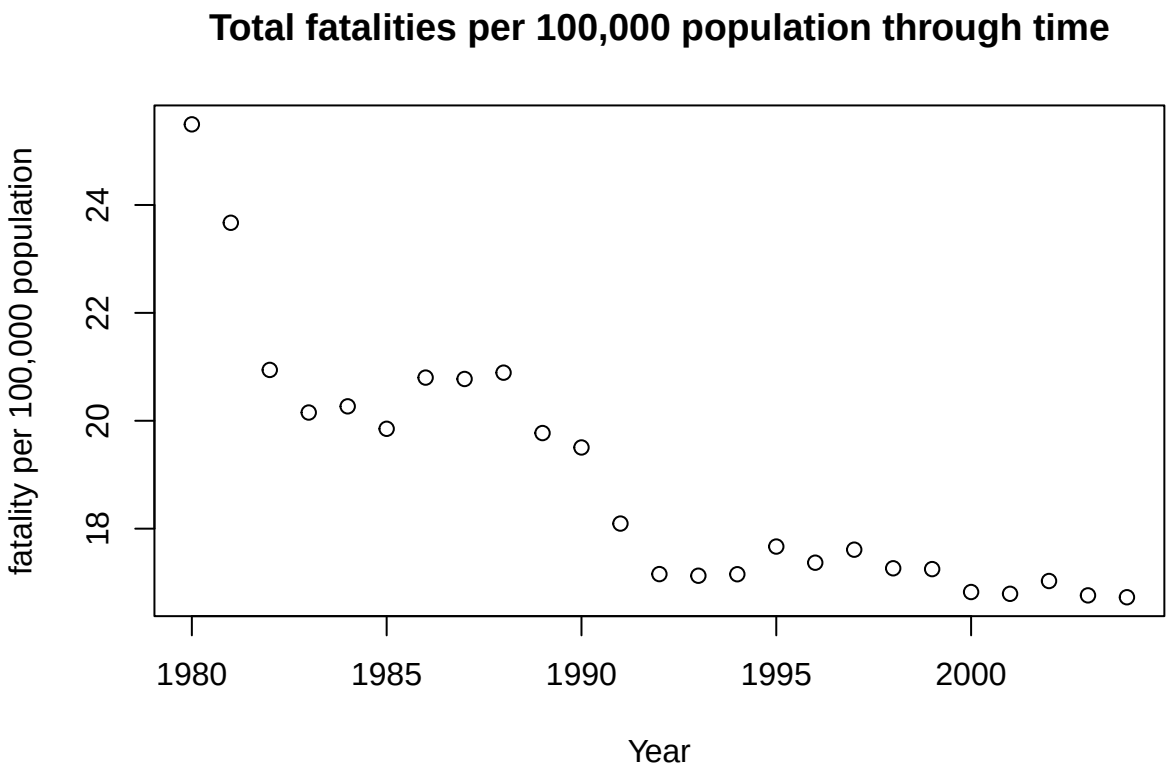



```
data_sub = data[, c('totfatrte', 'year')]
for (year in unique(data_sub$year)) {
  if (year == min(data_sub$year)) {
    next
  }
  data_sub[paste('year_', year, sep='')] = (data_sub$year == year) * 1
}
data_sub$year = NULL
mdl1 = lm('totfatrte ~ .', data=data_sub)
summary(mdl1)
```

```
##
## Call:
## lm(formula = "totfatrte ~ .", data = data_sub)
##
## 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 ***
```

```
## year_1981    -1.8244     1.2263  -1.488 0.137094
## year_1982    -4.5521     1.2263  -3.712 0.000215 ***
## year_1983    -5.3417     1.2263  -4.356 1.44e-05 ***
## year_1984    -5.2271     1.2263  -4.263 2.18e-05 ***
## year_1985    -5.6431     1.2263  -4.602 4.64e-06 ***
## year_1986    -4.6942     1.2263  -3.828 0.000136 ***
## year_1987    -4.7198     1.2263  -3.849 0.000125 ***
## year_1988    -4.6029     1.2263  -3.754 0.000183 ***
## year_1989    -5.7223     1.2263  -4.666 3.42e-06 ***
## year_1990    -5.9894     1.2263  -4.884 1.18e-06 ***
## year_1991    -7.3998     1.2263  -6.034 2.14e-09 ***
## year_1992    -8.3367     1.2263  -6.798 1.68e-11 ***
## year_1993    -8.3669     1.2263  -6.823 1.43e-11 ***
## year_1994    -8.3394     1.2263  -6.800 1.66e-11 ***
## year_1995    -7.8260     1.2263  -6.382 2.51e-10 ***
## year_1996    -8.1252     1.2263  -6.626 5.25e-11 ***
## year_1997    -7.8840     1.2263  -6.429 1.86e-10 ***
## year_1998    -8.2292     1.2263  -6.711 3.01e-11 ***
## year_1999    -8.2442     1.2263  -6.723 2.77e-11 ***
## year_2000    -8.6690     1.2263  -7.069 2.67e-12 ***
## year_2001    -8.7019     1.2263  -7.096 2.21e-12 ***
## year_2002    -8.4650     1.2263  -6.903 8.32e-12 ***
## year_2003    -8.7310     1.2263  -7.120 1.88e-12 ***
## 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
```

```
year_avg = as.numeric(mdl1$coefficients)
year_avg[2:length(year_avg)] = year_avg[2:length(year_avg)] + year_avg[1]
plot(unique(data$year), year_avg, main='Total fatalities per 100,000 population through time',
```



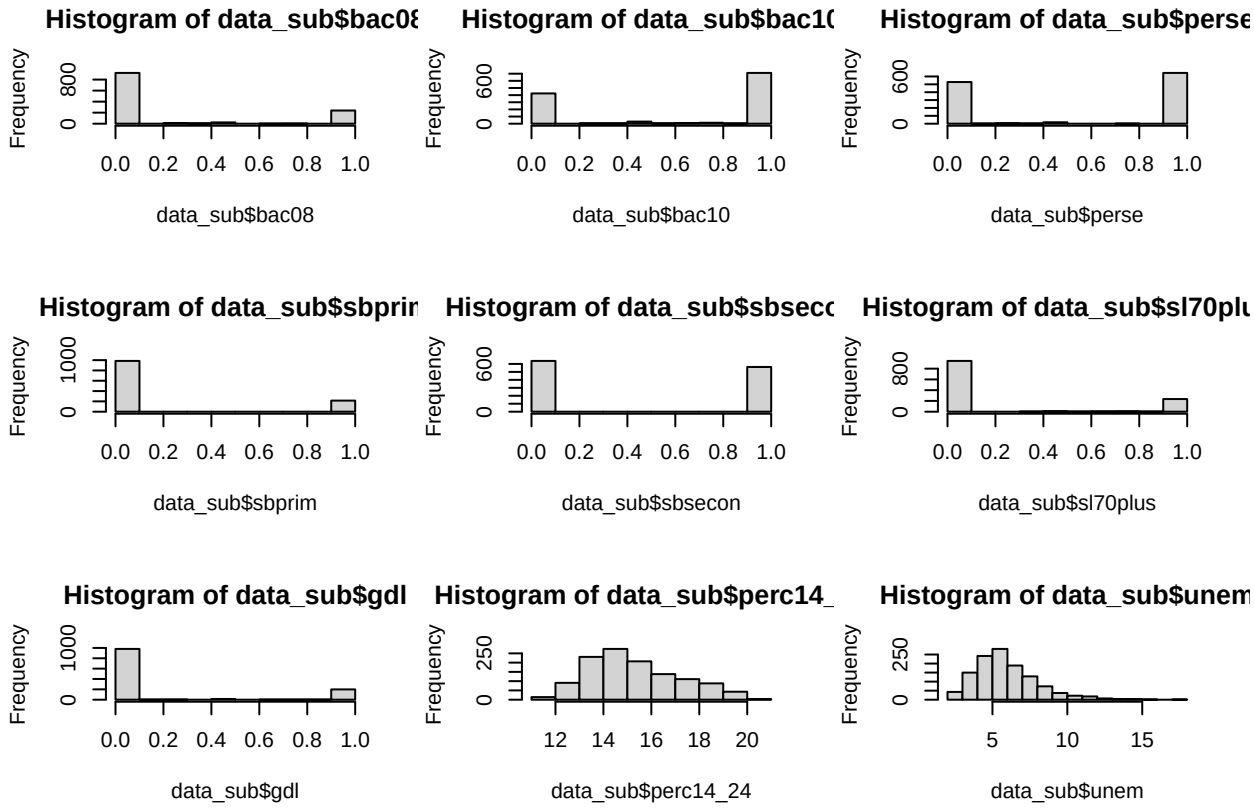
Response to Q2

The average fatalities per 100,000 people (totfatrte) for each year can be computed through the regression, where the fatalities are regressed on year dummy variables, and by skipping the first year since the intercept of the regression will represent the average for 1980, and all further coefficients will represent the adjustment to the intercept term to arrive at the average for that given year. Looking at the chart, we can see that the average fatalaties per 100,000 people have been trending down overall, with a big improvements in the early and late 1980's, as well as early 1990's, with only a minor improvement from then until 2004.

3. (15%) 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.)

```
vars = c('bac08', 'bac10', 'perse', 'sbprim', 'sbsecon', 'sl70plus', 'gdl', 'perc14_24', 'unem

for (var in vars) {
  data_sub[var] = data[var]
```

```
  #hist(data_sub[var])
}

par(mfrow=c(3,3))
hist(data_sub$bac08)
hist(data_sub$bac10)
hist(data_sub$perse)
hist(data_sub$sbprim)
hist(data_sub$sbsecon)
hist(data_sub$sl70plus)
hist(data_sub$gdl)
hist(data_sub$perc14_24)
hist(data_sub$unem)
```




```
#hist(data_sub$vehicmilespc)


data_sub$unem = log(data_sub$unem)
for (i in 1:7) {
  data_sub[vars[i]] = (data_sub[vars[i]] > 0.5) * 1
}
mdl2 = lm('totfatrte ~ .', data=data_sub)
```

```
summary(mdl2)
```

```
##
## Call:
## lm(formula = "totfatrte ~ .", data = data_sub)
##
## 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 **
## year_1981    -2.107e+00  8.229e-01  -2.560 0.010578 *
## year_1982    -6.304e+00  8.397e-01  -7.508 1.19e-13 ***
## year_1983    -7.190e+00  8.515e-01  -8.445  < 2e-16 ***
## year_1984    -5.826e+00  8.666e-01  -6.723 2.78e-11 ***
## year_1985    -6.458e+00  8.852e-01  -7.296 5.48e-13 ***
## year_1986    -5.634e+00  9.231e-01  -6.103 1.42e-09 ***
## year_1987    -6.065e+00  9.613e-01  -6.309 3.98e-10 ***
## year_1988    -6.176e+00  1.011e+00  -6.109 1.36e-09 ***
## year_1989    -7.688e+00  1.049e+00  -7.325 4.43e-13 ***
## year_1990    -8.682e+00  1.072e+00  -8.102 1.36e-15 ***
## year_1991    -1.087e+01  1.093e+00  -9.944  < 2e-16 ***
## year_1992    -1.263e+01  1.114e+00 -11.335  < 2e-16 ***
## year_1993    -1.250e+01  1.128e+00 -11.085  < 2e-16 ***
## year_1994    -1.208e+01  1.150e+00 -10.500  < 2e-16 ***
## year_1995    -1.147e+01  1.180e+00  -9.722  < 2e-16 ***
## year_1996    -1.340e+01  1.223e+00 -10.962  < 2e-16 ***
## year_1997    -1.352e+01  1.244e+00 -10.864  < 2e-16 ***
## year_1998    -1.420e+01  1.268e+00 -11.197  < 2e-16 ***
## year_1999    -1.415e+01  1.284e+00 -11.019  < 2e-16 ***
## year_2000    -1.440e+01  1.307e+00 -11.021  < 2e-16 ***
## year_2001    -1.567e+01  1.317e+00 -11.903  < 2e-16 ***
## year_2002    -1.649e+01  1.326e+00 -12.434  < 2e-16 ***
## year_2003    -1.692e+01  1.331e+00 -12.716  < 2e-16 ***
## year_2004    -1.633e+01  1.367e+00 -11.947  < 2e-16 ***
## bac08        -2.288e+00  4.858e-01  -4.709 2.79e-06 ***
## bac10        -1.256e+00  3.591e-01  -3.497 0.000489 ***
## perse        -5.625e-01  2.919e-01  -1.927 0.054231 .
## sbprim       -3.795e-01  4.898e-01  -0.775 0.438515
## sbsecon      -1.535e-01  4.279e-01  -0.359 0.719911
## sl70plus      3.112e+00  4.331e-01   7.186 1.19e-12 ***
## gdl          -3.014e-01  5.066e-01  -0.595 0.552051
## perc14_24     1.776e-01  1.222e-01   1.453 0.146542
## 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
```

```
anova(mdl1, mdl2, test="Chisq")
```

```
## Analysis of Variance Table
##
## Model 1: totfatrte ~ year_1981 + year_1982 + year_1983 + year_1984 + year_1985 +
##     year_1986 + year_1987 + year_1988 + year_1989 + year_1990 +
##     year_1991 + year_1992 + year_1993 + year_1994 + year_1995 +
##     year_1996 + year_1997 + year_1998 + year_1999 + year_2000 +
##     year_2001 + year_2002 + year_2003 + year_2004
## Model 2: totfatrte ~ year_1981 + year_1982 + year_1983 + year_1984 + year_1985 +
##     year_1986 + year_1987 + year_1988 + year_1989 + year_1990 +
##     year_1991 + year_1992 + year_1993 + year_1994 + year_1995 +
##     year_1996 + year_1997 + year_1998 + year_1999 + year_2000 +
##     year_2001 + year_2002 + year_2003 + year_2004 + bac08 + bac10 +
##     perse + sbprim + sbsecon + sl70plus + gdl + perc14_24 + unem +
##     vehicmilespc
##   Res.Df   RSS Df Sum of Sq  Pr(>Chi)
## 1   1175 42407
## 2   1165 18867 10     23540 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Response to Q3

Since bac08, bac10, perse, sbprim, sbsecon, s170plus and gdl, are 0-1 variables that represent the fraction of a year that a specific speed limit / blood alcohol level / law was in place for (for a given year), these are transformed into 0-1 hot encodings (0 = 0.50 or less, 1 if > 0.50) for better interpretability. Furthermore, the unem variable, which is the unemployment rate, is log transformed to take out the skew of its distribution as mentioned in the EDA. The remaining variables (perc14_14 and vehicmilespc) are not transformed since their distributions are not skewed.

After running the regression with the added variables, we can see from the anova (chi-square) test that the added variables are adding significant explanitory power to the model. bac08 and bac10 variables represent the blood alcohol level limits that are prescribed by law, and these two variables can either be 0 for both if there are no limits, 1 for one and 0 for the other, or a fractions that can sum to 1 if one limit was used for part of one year and the other was used for the remaining. The coefficients for these two variables in the regression are -2.288 and -1.256, which implies that total fatalities per 100,000 people decreases by these amounts when these limits are in place. Interestingly and not surprisingly, going from no limit to 0.08 limit reduces the fatalities more than going for 0.08 to 0.1. Both coefficients are significant at the 0.01 confidence level.

Looking at per se laws (perse), the coefficient is negative as expected, and specifically, the model estimates that by introducing this per se law, total fatalities per 100,000 people is reduced by -0.5625. This variable is somewhat significant at the 0.1 level. Moving to the primary seat belt law, there is also an estimated negative effect with total fatalities per 100,000 people of -0.3795, however, this variable does not seem significant, and interestingly, the sbsecon (secondary seal belt law), is not significant either and has an even lower magnititude in estimated effect on totfatrte.

4. (15%) 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?

```
#head(data)

# Transform the data (as per inputs from Dominik)
data$bac08bin = ifelse(data$bac08<=0.5,0,1)
data$bac10bin = ifelse(data$bac10<=0.5,0,1)
data$persebin = ifelse(data$perse<=0.5,0,1)
data$sbprimbin = ifelse(data$sbprim<=0.5,0,1)
data$sbseconbin = ifelse(data$sbsecon<=0.5,0,1)
data$sl70plusbin = ifelse(data$sl70plus<=0.5,0,1)
data$gdlbin = ifelse(data$gdl<0.5,0,1)
data$unemlog = log(data$unem)

#Fixed Effects Model
model.fe = plm(totfatrte~bac08bin+bac10bin+persebin+sbprimbin+sbseconbin+sl70plusbin+gdlbin+
                      perc14_24+unemlog+vehicmilespc + d81+d82+d83+d84+d85+d86+d87+d88+d89+
                      d90+d91+d92+d93+d94+d95+d96+d97+d98+d99+d00+d01+d02+d03+d04,
               data=data, model=c("within"), index=c('state','year'), effect = "twoways")
summary(model.fe)
```

```
## Twoways effects Within Model
##
## Call:
## plm(formula = totfatrte ~ bac08bin + bac10bin + persebin + sbprimbin +
##     sbseconbin + sl70plusbin + gdlbin + perc14_24 + unemlog +
##     vehicmilespc + d81 + d82 + d83 + d84 + d85 + d86 + d87 +
##     d88 + d89 + d90 + d91 + d92 + d93 + d94 + d95 + d96 + d97 +
##     d98 + d99 + d00 + d01 + d02 + d03 + d04, data = data, effect = "twoways",
##     model = c("within"), index = c("state", "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -8.261550 -1.041583 -0.019056  0.984573 14.642734
##
```

```
## Coefficients:
##                 Estimate  Std. Error t-value  Pr(>|t|)
## bac08bin     -1.10399614  0.33022452 -3.3432 0.0008557 ***
## bac10bin     -0.80560450  0.22564600 -3.5702 0.0003718 ***
## persebin     -1.12079848  0.22340455 -5.0169 6.104e-07 ***
## sbprimbin    -1.19280857  0.34308412 -3.4767 0.0005271 ***
## sbseconbin   -0.30877884  0.25213895 -1.2246 0.2209698
## sl70plusbin   0.05315694  0.26093278  0.2037 0.8386103
## gdlbin       -0.37500598  0.27964169 -1.3410 0.1801853
## perc14_24     0.16346044  0.09545138  1.7125 0.0870819 .
## unemlog      -3.71639544  0.39225223 -9.4745 < 2.2e-16 ***
## vehicmilespc  0.00094479  0.00011034  8.5629 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5928.9
## Residual Sum of Squares: 4549.2
## R-Squared:      0.23271
## Adj. R-Squared: 0.17711
## F-statistic: 33.9069 on 10 and 1118 DF, p-value: < 2.22e-16
```

Response to Q4

***How do the coefficients on* bac08, bac10, perse, and sbprim* compare with the pooled OLS estimates?** *

Answer to be provided based on model built by Dominik in Q3

Which set of estimates do you think is more reliable?

1. The FE model models the variation over time in $totfatrte$ and all the independent variables *within* each state

2. ################Points to be added based on model added in Q3

What assumptions are needed in each of these models? Are these assumptions reasonable in the current context?

FE Assumption - The fixed effect assumption is that the individual-specific effects are correlated with the independent variables.

Pooled OLS assumption - The Key assumption of Pooled OLS is that there are unique, time constant attributes of individuals that are not correlated with the individual regressors.

In the current context, it is very difficult to test assumption for Poole OLS model. In other words, FE model assumptions are more reasonable to proceed.

5. (10%) Would you perfer to use a random effects model instead of the fixed effects model you built in *Exercise 4*? Please explain.

```
model.re = plm(totfatrte~bac08bin+bac10bin+persebin+sbprimbin+sbseconbin+sl70plusbin+gdlbin+
                      perc14_24+unemlog+vehicmilespc + d81+d82+d83+d84+d85+d86+d87+d88+d89+
                      d90+d91+d92+d93+d94+d95+d96+d97+d98+d99+d00+d01+d02+d03+d04,
               data=data, model=c("random"), index=c('state','year'))

summary(model.re)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm(formula = totfatrte ~ bac08bin + bac10bin + persebin + sbprimbin +
##     sbseconbin + sl70plusbin + gdlbin + perc14_24 + unemlog +
##     vehicmilespc + d81 + d82 + d83 + d84 + d85 + d86 + d87 +
##     d88 + d89 + d90 + d91 + d92 + d93 + d94 + d95 + d96 + d97 +
##     d98 + d99 + d00 + d01 + d02 + d03 + d04, data = data, model = c("random"),
##     index = c("state", "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Effects:
##                  var std.dev share
## idiosyncratic 4.069   2.017 0.342
## individual    7.819   2.796 0.658
## theta: 0.8572
##
## Residuals:
##     Min.  1st Qu.   Median  3rd Qu.     Max.
## -8.41735 -1.21591 -0.16209  0.94795 16.39919
##
## Coefficients:
##                  Estimate  Std. Error  z-value  Pr(>|z|)
## (Intercept)   1.9880e+01  2.2639e+00   8.7814 < 2.2e-16 ***
## bac08bin     -1.2065e+00  3.4049e-01  -3.5434 0.0003950 ***
## bac10bin     -8.6902e-01  2.3321e-01  -3.7264 0.0001943 ***
## persebin     -1.0683e+00  2.2905e-01  -4.6640 3.100e-06 ***
## sbprimbin    -1.1434e+00  3.5286e-01  -3.2404 0.0011937 **
## sbseconbin   -3.0957e-01  2.6110e-01  -1.1856 0.2357635
## sl70plusbin   1.3203e-01  2.7008e-01   0.4889 0.6249426
## gdlbin       -3.4065e-01  2.9016e-01  -1.1740 0.2403837
## perc14_24     1.7892e-01  9.7841e-02   1.8286 0.0674526 .
## unemlog      -3.1341e+00  4.0073e-01  -7.8209 5.244e-15 ***
## vehicmilespc  1.1891e-03  1.0929e-04  10.8797 < 2.2e-16 ***
## d81          -1.6116e+00  4.3015e-01  -3.7465 0.0001793 ***
```

```
## d82          -3.5672e+00  4.5056e-01  -7.9172 2.429e-15 ***
## d83          -4.2443e+00  4.6221e-01  -9.1826 < 2.2e-16 ***
## d84          -4.6567e+00  4.7702e-01  -9.7620 < 2.2e-16 ***
## d85          -5.1300e+00  4.9800e-01 -10.3012 < 2.2e-16 ***
## d86          -4.1427e+00  5.3277e-01  -7.7759 7.493e-15 ***
## d87          -4.8456e+00  5.7325e-01  -8.4528 < 2.2e-16 ***
## d88          -5.3904e+00  6.2372e-01  -8.6423 < 2.2e-16 ***
## d89          -6.7373e+00  6.6286e-01 -10.1639 < 2.2e-16 ***
## d90          -6.8719e+00  6.8557e-01 -10.0238 < 2.2e-16 ***
## d91          -7.6375e+00  7.0062e-01 -10.9011 < 2.2e-16 ***
## d92          -8.5935e+00  7.2137e-01 -11.9127 < 2.2e-16 ***
## d93          -8.9144e+00  7.3512e-01 -12.1264 < 2.2e-16 ***
## d94          -9.3465e+00  7.5459e-01 -12.3862 < 2.2e-16 ***
## d95          -9.1062e+00  7.8024e-01 -11.6710 < 2.2e-16 ***
## d96          -9.5842e+00  8.2246e-01 -11.6530 < 2.2e-16 ***
## d97          -9.8431e+00  8.4367e-01 -11.6669 < 2.2e-16 ***
## d98          -1.0564e+01  8.6460e-01 -12.2180 < 2.2e-16 ***
## d99          -1.0769e+01  8.7732e-01 -12.2754 < 2.2e-16 ***
## d00          -1.1361e+01  8.9168e-01 -12.7414 < 2.2e-16 ***
## d01          -1.0985e+01  8.9318e-01 -12.2989 < 2.2e-16 ***
## d02          -1.0261e+01  8.9371e-01 -11.4813 < 2.2e-16 ***
## d03          -1.0335e+01  8.9485e-01 -11.5491 < 2.2e-16 ***
## d04          -1.0715e+01  9.2133e-01 -11.6301 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    12878
## Residual Sum of Squares: 5131.3
## R-Squared:      0.60155
## Adj. R-Squared: 0.58992
## Chisq: 1758.8 on 34 DF, p-value: < 2.22e-16
```

Response to Q5

1. In a random effects model, the unobserved variables are assumed to be uncorrelated with (or, more strongly, statistically independent of) all the observed variables.

2. In a fixed effects model, the unobserved variables are allowed to have any associations whatsoever with the observed variables.

3. For the given data, assumption for fixed effect model seems to be more practical as it is very difficult to test/prove that unobserved variables are not correlated with observed variables if we use random effect modeling. On other hand, it is possible to remove omitted/unobserved variable bias using fixed effects modeling with dummy variables of each year to explain the unaccounted for time-variant error dependence.

4. Hence, fixed effect model is prferred over random effect model.

6. (10%) 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.

Response to Q6

1. From the FE model, the coefficient for the *vehicmilespc* variable is 0.00094479

2. $totfatrte$ is Fatalities/100K people per mile-driven/capita.

3. If *vehicmilespc* increases by $1,000$, the value of $totfatrte$ increases as follows

$$Increase - In - totfatrte - value = 1000 * 0.00094479 = 0.94479$$

4. In summary, estimated effect on *totfatrte vehicmilespc*, if the number of miles driven per capita, increases by $1,000$, is an increase in it's value by 0.94479 (provided all other things do not change)

7. (5%) 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?

Response for Q7

1. With, positive serial correlation, the OLS estimates of ths standard errors will be smaller than the true standard errors. This willlead to the conclusion that the parameter estimates are more precise than they really are. There will be a tendency to reject the null hypothesis when it should not be rejected. In other words, we will consider insignificant variables as significant.

2. On the rcontrary, with the presence of heteroskedasticity in our error, we will fail to reject null hypothesis when it should be rejected. In other words, we will not be in a position to detect the significance of potentially valuable regressor.