

# Lab 3: Panel Models

## US Traffic Fatalities: 1980 - 2004

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### 1 U.S. traffic fatalities: 1980-2004

In this lab, we are asking you to answer the following **causal** question:

**“Do changes in traffic laws affect traffic fatalities?”**

To answer this question, please complete the tasks specified below using the data provided in `data/driving.Rdata`. This data 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 also provided in the dataset.

```
load(file="./data/driving.RData")

## please comment these calls in your work
#glimpse(data)
#desc
```

## 2 (30 points, total) Build and Describe the Data

```
# For the fractions, we are taking the majority as a speed limit
# We skipped year_of_observation since there a year column which aligns with dx
df <- data %>%
  mutate(speed_limit = ifelse(sl55 >= 0.5, '55',
                              ifelse(sl65 >= 0.5, '65',
                              ifelse(sl70 >= 0.5, '70',
                              ifelse(sl75 >= 0.5, '75',
                              ifelse(slnone >= 0.5, 'none', '0')
                              ))))) %>%
    mutate(speed_limit=factor(speed_limit,
                              levels=c('55', '65', '70', '75', 'none')),
           blood_alcohol_limit_10 = ifelse(bac10 >= 0.5, 1, 0),
           blood_alcohol_limit_08 = ifelse(bac08 >= 0.5, 1, 0)) %>%
  mutate(bac=ifelse(blood_alcohol_limit_10==1, '10',
                    ifelse(blood_alcohol_limit_08==1, '8', 'none'))) %>%
  mutate(bac=factor(bac, levels=c('none', '10', '8'))) %>%
  select(!c((sl55:slnone), (d80:d04), bac10, bac08)) %>% # Excluding
  rename(minimum_drinking_age = minage, zero_tolerance_law = zerotol,
         graduated_drivers_license_law = gdl, per_se_law = perse,
         total_fatalities = totfat, nighttime_fatalities = nghtfat,
         weekend_fatalities = wkndfat, total_fatalities_per_100M_miles = totfatpvm,
         nighttime_fatalities_per_100M_miles = nghtfatpvm,
         weekend_fatalities_per_100M_miles = wkndfatpvm,
         state_population = statepop, total_fatalities_rate = totfatrte,
         nighttime_fatalities_rate = nghtfatrte,
         weekend_fatalities_rate = wkndfatrte,
         vehicle_miles_traveled = vehicmiles, unemployment_rate = unem,
         population_aged_14_to_24_rate = perc14_24,
         speed_limit_70_plus = sl70plus,
         seat_belt = seatbelt,
         primary_seatbelt_law = sbprim, secondary_seatbelt_law = sbsecon,
         miles_driven_per_capita = vehicmilespc) %>%
  mutate(speed_limit_70_plus =
         ifelse(speed_limit_70_plus>0.5, 1, 0)
         ) %>%
  mutate(seat_belt_law =
         ifelse(seat_belt==0, 'none',
         ifelse(seat_belt==2, 'secondary',
         ifelse(seat_belt==1, 'primary', 'na')))) %>%
  mutate(seat_belt_law=factor(seat_belt_law,
                              levels=c('none', 'secondary', 'primary')),
         ) %>%
  mutate(per_se_law=round(per_se_law, 0)) %>%
```

```

mutate(per_se_low=factor(per_se_low, levels=c(0, 1)))

# Adding states to the dataframe
state_df <- data.frame("index" = 1:51,
                       "state_name" = sort(c(state.name, "District of Columbia")))
main_df <- merge(df, state_df, by.x = 'state', by.y = 'index')

pdata <- pdata.frame(main_df, index=c("state", "year"))
head(main_df)

```

```

##   state year seat_belt minimum_drinking_age zero_tolerance_low
## 1     1 1980         0             18                0
## 2     1 1981         0             18                0
## 3     1 1982         0             18                0
## 4     1 1983         0             18                0
## 5     1 1984         0             18                0
## 6     1 1985         0             20                0
##   graduated_drivers_license_low per_se_low total_fatalities
## 1                        0         0           940
## 2                        0         0           933
## 3                        0         0           839
## 4                        0         0           930
## 5                        0         0           932
## 6                        0         0           882
##   nighttime_fatalities weekend_fatalities total_fatalities_per_100M_miles
## 1                422             236                3.20
## 2                434             248                3.35
## 3                376             224                2.81
## 4                397             223                3.00
## 5                421             237                2.83
## 6                358             224                2.51
##   nighttime_fatalities_per_100M_miles weekend_fatalities_per_100M_miles
## 1                1.437                0.803
## 2                1.558                0.890
## 3                1.259                0.750
## 4                1.281                0.719
## 5                1.278                0.720
## 6                1.019                0.637
##   state_population total_fatalities_rate nighttime_fatalities_rate
## 1        3893888         24.14         10.84
## 2        3918520         24.07         11.08
## 3        3925218         21.37          9.58
## 4        3934109         23.64         10.09
## 5        3951834         23.58         10.65
## 6        3972527         22.20          9.01
##   weekend_fatalities_rate vehicle_miles_traveled unemployment_rate
## 1                6.06         29.37500                8.8
## 2                6.33         27.85200               10.7
## 3                5.71         29.85765               14.4
## 4                5.67         31.00000               13.7
## 5                6.00         32.93286               11.1
## 6                5.64         35.13944                8.9

```

```
## population_aged_14_to_24_rate speed_limit_70_plus primary_seatbelt_law
## 1 18.9 0 0
## 2 18.7 0 0
## 3 18.4 0 0
## 4 18.0 0 0
## 5 17.6 0 0
## 6 17.3 0 0
## secondary_seatbelt_law miles_driven_per_capita speed_limit
## 1 0 7543.874 55
## 2 0 7107.785 55
## 3 0 7606.622 55
## 4 0 7879.802 55
## 5 0 8333.562 55
## 6 0 8845.614 55
## blood_alcohol_limit_10 blood_alcohol_limit_08 bac seat_belt_law state_name
## 1 1 0 10 none Alabama
## 2 1 0 10 none Alabama
## 3 1 0 10 none Alabama
## 4 1 0 10 none Alabama
## 5 1 0 10 none Alabama
## 6 1 0 10 none Alabama
```

```
# Time series line plot
# Variable to plot as var_name
# Each line gets a color based on the group_name
# X-axis is always year
plots.ts.by.group <- function(df, var_name, group_name, subtitle='') {
  plt <- df %>%
    mutate(!group_name := factor(df[[group_name]])) %>%
    ggplot(aes_string(x='year', y=var_name, group='state')) +
    geom_line(aes_string(color=group_name)) +
    labs(subtitle=subtitle) +
    theme(legend.position = c(0.8, 0.8), legend.key.size = unit(0.2, "cm"),
          legend.text=element_text(size=rel(0.5)),
          legend.title=element_text(size=rel(0.7)))
  return((plt))
}

# Box plot by group
# Variable to plot as var_name
# Each group is split by group_name
plots.box.by.group <- function(df, var_name, group_name, subtitle='')
{
  plt <- df %>% mutate(factored=factor(df[[group_name]])) %>%
    ggplot(aes_string(x='factored', y=var_name)) +
    geom_boxplot(outlier.colour="red", outlier.shape=8, outlier.size=4) +
    theme(axis.text.x=element_text(angle=-90)) +
    labs(subtitle=subtitle) +
    xlab(group_name)
  return((plt))
}
```

```

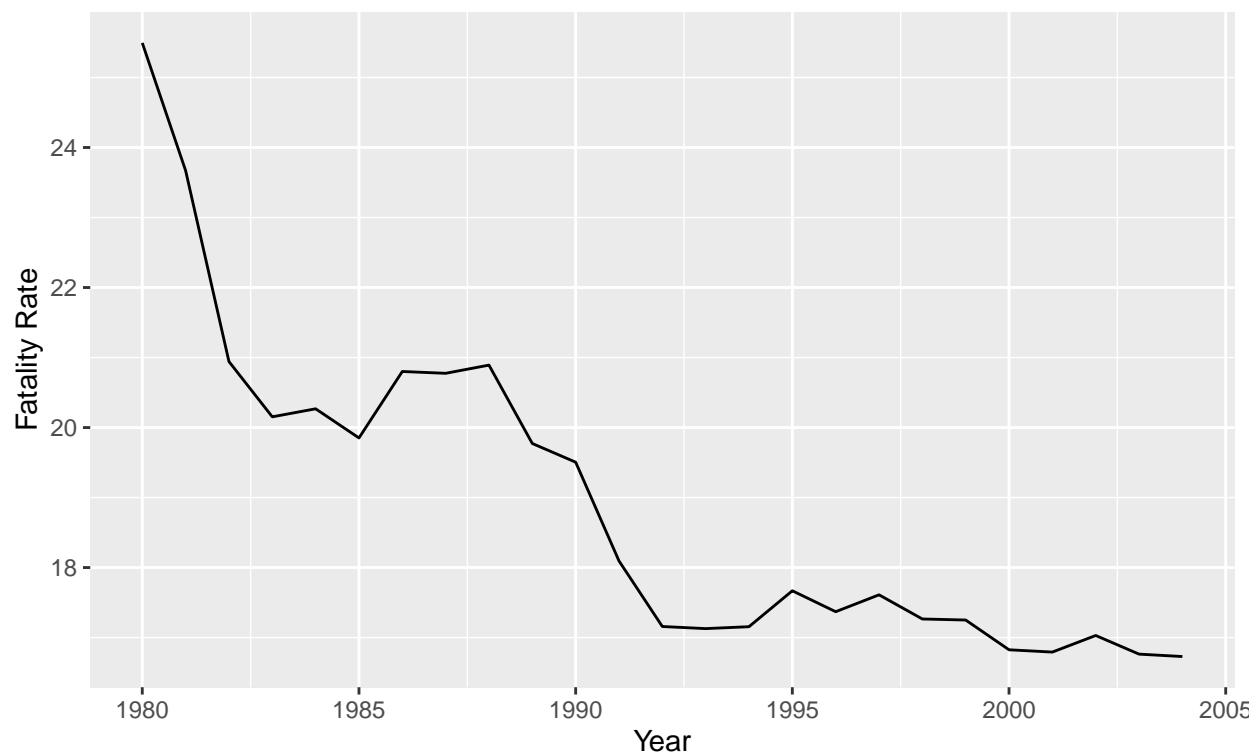
# Time series line plot
# Variable to plot as var_name
# Each line gets a color based on the group_name
# X-axis is always year
plots.scatter.by.state <- function(df, var_name, subtitle='') {
  plt <- df %>%
    ggplot(aes_string(x=var_name, y='total_fatalities_rate')) +
    geom_point(aes(color=state_name)) +
    geom_smooth(method = lm, formula = y ~ x) +
    labs(subtitle=subtitle) +
    theme(legend.position = 'none')
  return((plt))
}

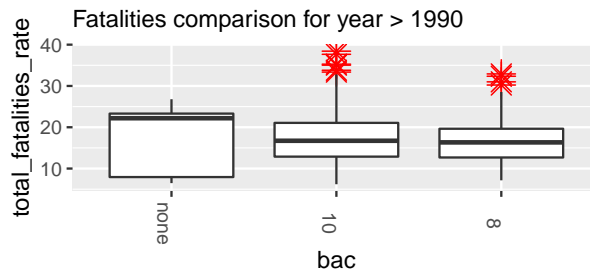
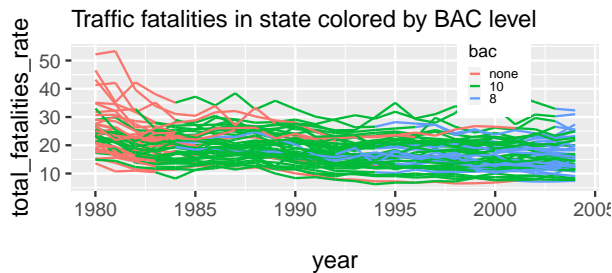
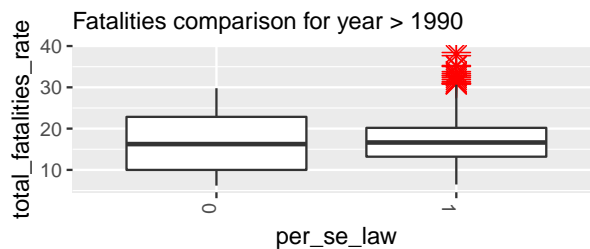
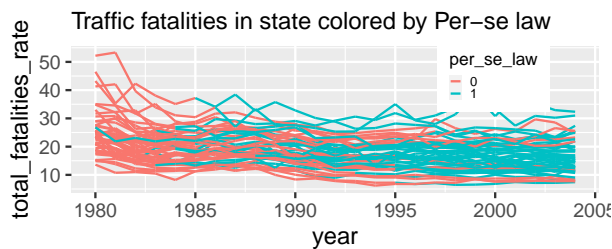
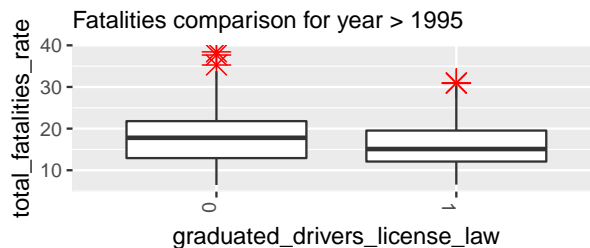
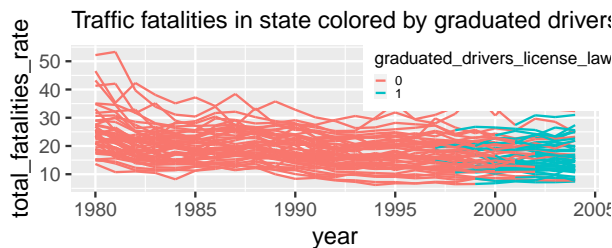
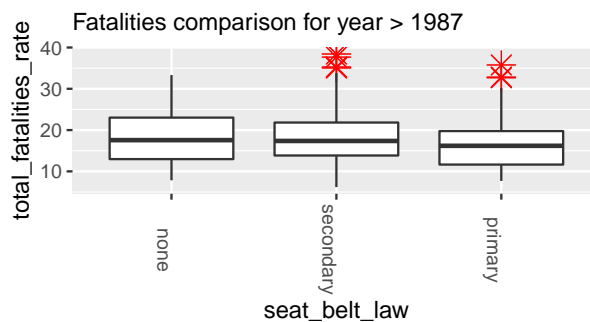
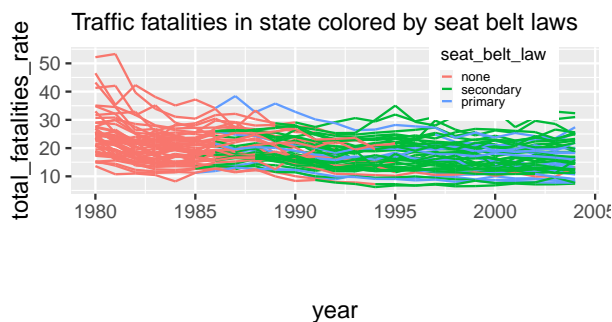
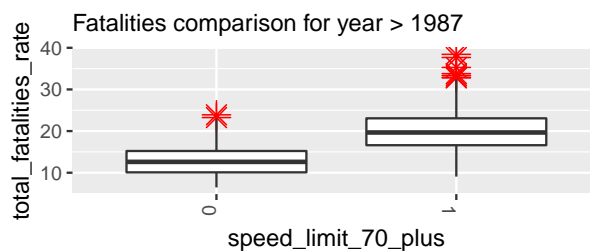
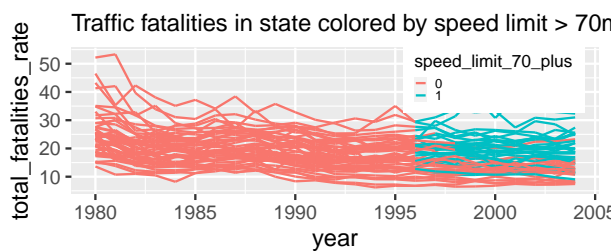
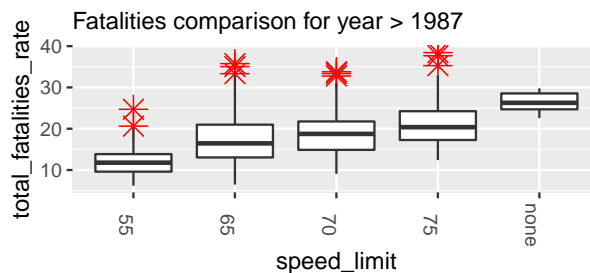
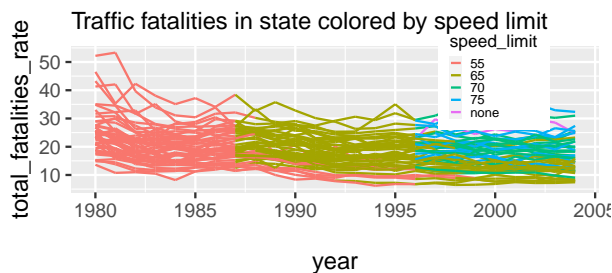
```

## 2.1 Main Plots

Average mean fatality rate across US

Fatality rate is going down





## 2.2 Description of variables

### 2.2.1 Factor variables

The highway speed limit was uniformly 55mph across all states before 1987. Since then, different states have adopted different speed limits. Especially in 1997, there was a significant increase in highway speeds across multiple states. The box plot compares the fatality rate across different speed limits filtered for years greater than 1987. We see that increasing speed limits are associated with increased fatality rates. As there are states with no speed limit, this variable has been treated as a factor.

Now thresholding speed limits for greater or lower than 70mph shows a similar pattern of higher speeds associated with a higher fatality rate.

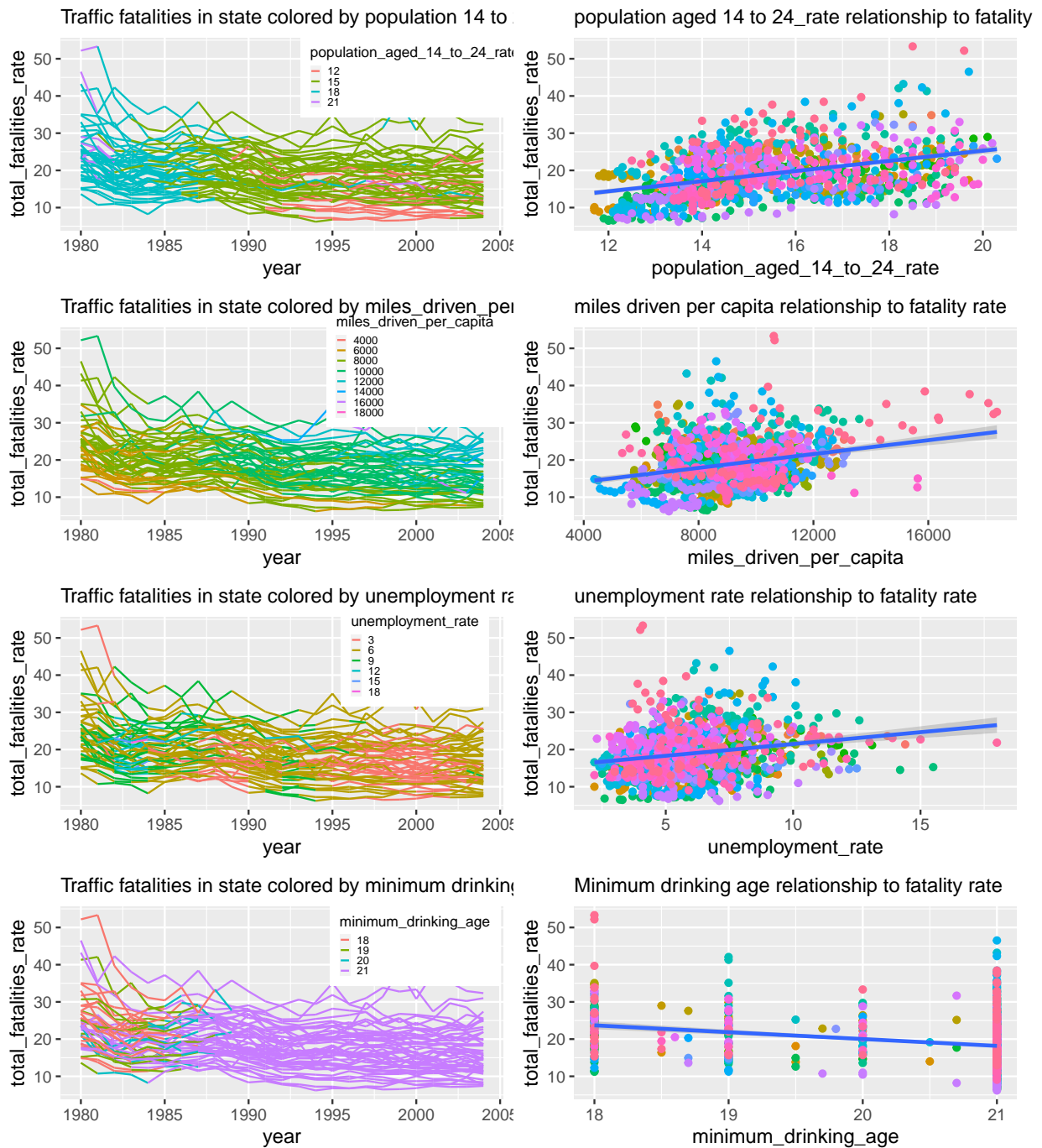
Seat belts started to become mandatory starting mid to late 80s and today there is only one state which does not have it as mandatory. Primary laws are the strictest and allow police to ticket drivers and passengers who are not wearing a proper safety restraint, even if that is the only traffic violation they are committing. Secondary seat belt laws, on the other hand, do not grant law enforcement officials the right to ticket drivers or passengers for failing to wear a safety restraint unless another traffic violation has occurred. There are 15 states with secondary seat belt laws. Source: <https://www.cooper-law-firm.com/what-is-the-difference-between-primary-and-secondary-seat-belt-laws/>.

The graduated drivers licence law was started to be introduced in the late 90's. The box plot, which has been filtered for years greater than 1995, suggests that even for that time frame, there is a reduction in fatality rate between the two groups.

Some states had Per-Se laws before the start of the data in 1980 and some still did not have Per-Se laws in 2004. There is a gradual increase in the adoption of the law from 1980 to about the 2000s. Surprisingly, there is an increase in fatality rates in comparison of data with PerSe law as compared to without.

Most states had adopted a BAC limit by the mid 80s with two states choosing a limit only in 2002.

## 2.2.2 Description of continous variables



There is a decrease in the percentage of 14 to 24 year olds in the population over time. This is correlated to the decrease in the fatalities during that time period.

Miles driven per capita also has a positive relationship with fatality rate. An increase in miles driven is associated with an increase in fatality rate

There is an increase in failure rate with an increase in unemployment rate.

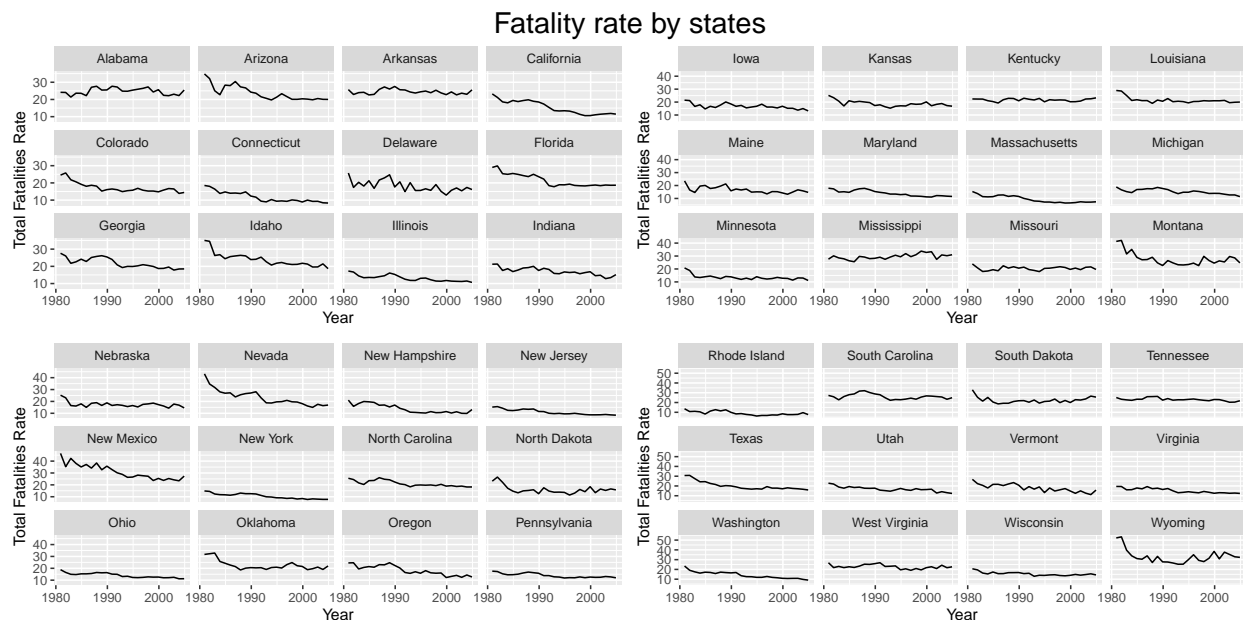


The minimum drinking age has been 21 in most states since the late 80s. There is a general decrease in fatality rate with an increased minimum drinking age but there also has been a general decrease in fatality rates during the time period when the age limits were changed.

```
cut_point <- c(-1, 12, 24, 36, 48)
plots <- vector('list', 4)

for (i in 2:5) {
  plots[[i-1]] <- (pdata %>%
    filter(as.integer(state) > cut_point[i-1] & as.integer(state) <= cut_point[i]) %>%
    ggplot(aes(x = as.Date(year,"%Y"), y = total_fatalities_rate)) +
    geom_line() +
    facet_wrap(~ state_name, nrow = 3, ncol=4) +
    labs(x = "Year", y = "Total Fatalities Rate") +
    theme(legend.position = "none"))
}

grid.arrange(plots[[1]], plots[[2]], plots[[3]], plots[[4]], nrow = 2, ncol = 2,
  top = textGrob("Fatality rate by states", gp=gpar(fontsize=20)))
```



> 'For most states, fatality rates go down over the years, but some states like Alabama and Arkansas do not show many changes. Surprisingly, Mississippi has an increase in the fatality rate.'

```
# traffic laws that we are exploring are seat_belt, minimum_drinking_age,
# zero_tolerance_law, graduated_drivers_license_law, per_se_law, speed_limit,
# speed_limit_70_plus, primary_seatbelt_law, secondary_seatbelt_law,
# blood_alcohol_limit_10, blood_alcohol_limit_08
```

### 3 (15 points) Preliminary Model

Estimate a linear regression model of *totfatrt* on a set of dummy variables for the years 1981 through 2004 and interpret what you observe. In this section, you should address the following tasks:

- Why is fitting a linear model a sensible starting place?
- What does this model explain, and what do you find in this model?
- Did driving become safer over this period? Please provide a detailed explanation.
- What, if any, are the limitation of this model. In answering this, please consider **at least**:
  - Are the parameter estimates reliable, unbiased estimates of the truth? Or, are they biased due to the way that the data is structured?
  - Are the uncertainty estimate reliable, unbiased estimates of sampling based variability? Or, are they biased due to the way that the data is structured?

```
pooled_ols <- plm(total_fatalities_rate ~ year, data = pdata,
                  index = c("state", "year"),
                  effect = "individual", model = "pooling")
summary(pooled_ols)
```

```
## Pooling Model
##
## Call:
## plm(formula = total_fatalities_rate ~ year, data = pdata, effect = "individual",
##      model = "pooling", index = c("state", "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##      Min.      1st Qu.      Median      3rd Qu.      Max.
## -12.93021  -4.34682   -0.73052    3.74875   29.64979
##
## Coefficients:
##              Estimate Std. Error t-value Pr(>|t|)
## (Intercept)  25.49458    0.86712  29.4015 < 2.2e-16 ***
## year1981     -1.82438    1.22629  -1.4877 0.1370936
## year1982     -4.55208    1.22629  -3.7121 0.0002152 ***
## year1983     -5.34167    1.22629  -4.3560 1.440e-05 ***
## year1984     -5.22708    1.22629  -4.2625 2.183e-05 ***
## year1985     -5.64313    1.22629  -4.6018 4.644e-06 ***
## year1986     -4.69417    1.22629  -3.8279 0.0001360 ***
## year1987     -4.71979    1.22629  -3.8488 0.0001251 ***
## year1988     -4.60292    1.22629  -3.7535 0.0001829 ***
## year1989     -5.72229    1.22629  -4.6663 3.418e-06 ***
## year1990     -5.98938    1.22629  -4.8841 1.182e-06 ***
## year1991     -7.39979    1.22629  -6.0343 2.137e-09 ***
## year1992     -8.33667    1.22629  -6.7983 1.681e-11 ***
## year1993     -8.36688    1.22629  -6.8229 1.425e-11 ***
## year1994     -8.33938    1.22629  -6.8005 1.656e-11 ***
## year1995     -7.82604    1.22629  -6.3819 2.512e-10 ***
## year1996     -8.12521    1.22629  -6.6258 5.246e-11 ***
## year1997     -7.88396    1.22629  -6.4291 1.863e-10 ***
## year1998     -8.22917    1.22629  -6.7106 3.007e-11 ***
## year1999     -8.24417    1.22629  -6.7228 2.774e-11 ***
## year2000     -8.66896    1.22629  -7.0692 2.666e-12 ***
## year2001     -8.70188    1.22629  -7.0961 2.214e-12 ***
## year2002     -8.46500    1.22629  -6.9029 8.316e-12 ***
## year2003     -8.73104    1.22629  -7.1199 1.877e-12 ***
## year2004     -8.76563    1.22629  -7.1481 1.542e-12 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    48612
## Residual Sum of Squares: 42407
## R-Squared:      0.12765
## Adj. R-Squared: 0.10983
## F-statistic: 7.16387 on 24 and 1175 DF, p-value: < 2.22e-16
```

‘Starting from a linear model will give us an easy and intuitively clearer overall pattern over the years via the coefficients on the year dummy variables (or instead by adding group ids as dummy variables) using controlling for any variable of interest, if any. Later on, when we perform panel data analysis, we can compare it against the linear model, justify the result and keep building the intuition on top of the linear model.’

‘This model explains the fatality rate over different years compared to the baseline year, which is 1980. All coefficients except for the 1981 year are statistically significant. From this model, we learn that in all years following the baseline up to 2004, the fatality rate goes down compared to the baseline year 1980. The decline increases as the year increases but not consistently, as seen, for example, between 1986 - 1988, where the fatality rate increases compared to previous years. However, it returns to the decline track/trend in 1989. The decrease in coefficients over the years means that driving becomes safer as the fatality rate keeps decreasing. For example, the fatality rate, which was 25.5 as of 1980, became 19.5 in 1990, 16.8 in 2000, and 16.7 in 2004, showing that driving over the years has become safer. In other words, around 8.8 fewer people are predicted to get traffic fatalities out of 100,000 people in 2004 than in 1980.’

‘We are ignoring unobserved Heterogeneity and the group structure by taking each entry as a separate observation. Because of that, residuals generally correlate across time and have heteroskedasticity across and/or within groups. Heteroscedastic residuals are a violation of the OLS Homoscedasticity assumption, which will make it difficult to trust the standard error. As a result, the confidence interval can not be trusted as it can be too wide or narrow. Also, the independence assumption (no autocorrelation) is violated since we did not accommodate the lag/trend component, which makes the OLS estimates to be unreliable; in other words, our OLS estimator is not the Best Linear Unbiased Estimator.’

## 4 (15 points) Expanded Model

### 4.1 Transformation(treatment) of variables

States where highway speeds were made over 70mph during the middle of the year contained a fractional value for that year. The fraction was thresholded at 0.5 to make this a binary variable. As there is no meaningful interpretation for this variable as a continuous value, this thresholding was necessary to convert it into a factor.

A state can have a primary, secondary or no seat belt laws. The `seat_belt_law` reflects these three factors combined into one variable.

Graduated drivers licence law and per-se law parameters both have fractional value for years where the law was implemented mid-year. The fractions were thresholded at 0.5 to make this a binary variable. As there is no meaningful interpretation for these variables as a continuous value, this thresholding was necessary to convert them into a factor.

Although Blood alcohol content (BAC) levels of 8PPM or 10PPM lends itself to a numeric interpretation, there is no numeric value associated with no BAC limit. For this reason BAC has been treated as a factor variable with levels none, 10 and 8.

None of the continuous variables, namely, unemployment rate, miles drive per capita, rate of 14 to 24 aged people in population required any transformation. This can be seen in the correlation plots in Figure y.

```
expanded.ols.data <- main_df %>% select(c(total_fatalities_rate, bac, per_se_law,
    seat_belt_law, graduated_drivers_license_law,
    population_aged_14_to_24_rate, minimum_drinking_age,
    unemployment_rate, speed_limit_70_plus,
    miles_driven_per_capita, year, state
))

main_p <- pdata.frame(expanded.ols.data, index=c("state", "year"))
expanded.ols <- plm(total_fatalities_rate ~ year + bac +
    population_aged_14_to_24_rate + miles_driven_per_capita +
    unemployment_rate + speed_limit_70_plus + per_se_law +
    seat_belt_law + graduated_drivers_license_law,
    data = main_p,
    index = c("state", "year"),
    effect = "individual", model = "pooling")
```

As we have used an OLS regression for a time series, we expect the residuals to be correlated. We perform a Ljung-Box test to check this. The Null hypothesis is that the series is not autocorrelated and the alternate hypothesis is that the series is autocorrelated. We test with an of  $\alpha = 0.05$ .

```
expanded.ols %>% residuals() %>% Box.test(type='Ljung-Box') -> lb.res
```

With a p value of 0 less than  $\alpha$ , we reject the Null hypothesis that the series is not auto-correlated. As the residuals are autocorrelated, the standard error of the parameters cannot be trusted. We review the model parameters with this in mind.

```
summary(expanded.ols)
```

```
## Pooling Model
##
## Call:
## plm(formula = total_fatalities_rate ~ year + bac + population_aged_14_to_24_rate +
##     miles_driven_per_capita + unemployment_rate + speed_limit_70_plus +
##     per_se_law + seat_belt_law + graduated_drivers_license_law,
##     data = main_p, effect = "individual", model = "pooling",
##     index = c("state", "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##      Min.   1st Qu.   Median   3rd Qu.    Max.
## -14.99024  -2.73218  -0.28596   2.28551  21.43864
##
## Coefficients:
```

```

##               Estimate Std. Error t-value Pr(>|t|)
## (Intercept)    -2.8620e+00  2.4767e+00  -1.1556  0.2481001
## year1981       -2.1794e+00  8.2897e-01  -2.6291  0.0086750 **
## year1982       -6.6054e+00  8.5501e-01  -7.7256  2.391e-14 ***
## year1983       -7.4082e+00  8.7272e-01  -8.4887 < 2.2e-16 ***
## year1984       -5.8639e+00  8.7891e-01  -6.6718  3.896e-11 ***
## year1985       -6.5178e+00  8.9607e-01  -7.2737  6.405e-13 ***
## year1986       -5.8901e+00  9.3184e-01  -6.3209  3.697e-10 ***
## year1987       -6.4048e+00  9.6818e-01  -6.6153  5.639e-11 ***
## year1988       -6.6423e+00  1.0148e+00  -6.5452  8.886e-11 ***
## year1989       -8.1081e+00  1.0540e+00  -7.6926  3.056e-14 ***
## year1990       -9.0054e+00  1.0782e+00  -8.3526 < 2.2e-16 ***
## year1991       -1.1119e+01  1.1027e+00 -10.0836 < 2.2e-16 ***
## year1992       -1.2929e+01  1.1240e+00 -11.5031 < 2.2e-16 ***
## year1993       -1.2794e+01  1.1377e+00 -11.2456 < 2.2e-16 ***
## year1994       -1.2439e+01  1.1578e+00 -10.7438 < 2.2e-16 ***
## year1995       -1.1972e+01  1.1847e+00 -10.1059 < 2.2e-16 ***
## year1996       -1.3944e+01  1.2269e+00 -11.3652 < 2.2e-16 ***
## year1997       -1.4172e+01  1.2466e+00 -11.3689 < 2.2e-16 ***
## year1998       -1.5026e+01  1.2659e+00 -11.8698 < 2.2e-16 ***
## year1999       -1.5068e+01  1.2836e+00 -11.7388 < 2.2e-16 ***
## year2000       -1.5422e+01  1.3045e+00 -11.8216 < 2.2e-16 ***
## year2001       -1.6223e+01  1.3308e+00 -12.1900 < 2.2e-16 ***
## year2002       -1.6762e+01  1.3438e+00 -12.4736 < 2.2e-16 ***
## year2003       -1.7115e+01  1.3508e+00 -12.6705 < 2.2e-16 ***
## year2004       -1.6735e+01  1.3807e+00 -12.1207 < 2.2e-16 ***
## bac10          -1.3402e+00  3.8987e-01  -3.4375  0.0006078 ***
## bac8           -2.3824e+00  5.2609e-01  -4.5285  6.550e-06 ***
## population_aged_14_to_24_rate  1.4460e-01  1.2285e-01   1.1770  0.2394512
## miles_driven_per_capita      2.9312e-03  9.4938e-05  30.8747 < 2.2e-16 ***
## unemployment_rate           7.6061e-01  7.8004e-02   9.7509 < 2.2e-16 ***
## speed_limit_70_plus         3.2114e+00  4.3495e-01   7.3834  2.930e-13 ***
## per_se_low1                -6.3533e-01  2.9488e-01  -2.1546  0.0313996 *
## seat_belt_lowsecondary       6.9102e-02  4.2989e-01   0.1607  0.8723233
## seat_belt_lowprimary        -6.7320e-02  4.9157e-01  -0.1369  0.8910941
## graduated_drivers_license_low -4.1681e-01  5.2772e-01  -0.7898  0.4297853
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    48612
## Residual Sum of Squares: 19129
## R-Squared:              0.6065
## Adj. R-Squared: 0.59501
## F-statistic: 52.8112 on 34 and 1165 DF, p-value: < 2.22e-16

```

## 4.2 Interpretation of results

### 4.2.1 How are the blood alcohol variables defined? Interpret the coefficients that you estimate for this concept.

In an earlier section we have defined our treatment of the BAC variable as a factor with levels none, 10 and 8. In this model we note that the base level is no blood alcohol limit. We also note that bac value of 0.1% and 0.08% are both statistically significant parameters. The model

suggests that setting a blood alcohol limit of 0.1% is associated with a 1.34 unit decrease in fatality rate as compared to no BAC limit. The model suggests that a setting a blood alcohol limit of 0.08% is associated with a 2.38 unit decrease in fatality rate as compared to no BAC limit.

#### 4.2.2 Do *per se* laws have a negative effect on the fatality rate?

We note that per-se law is a statistically significant parameter. The model suggests that havng a per-se law is associated with a 0.64 unit decrease in fatality rate as compared to not having per-se law.

#### 4.2.3 Does having a primary seat belt law reduce fatality rates?

We note that the seat belt law factors are not statistically significant.

## 5 (15 points) State-Level Fixed Effects

Re-estimate the **Expanded Model** using fixed effects at the state level.

Model estimation for a fixed effect(within) model.

```
expanded.within <- plm(total_fatalities_rate ~ bac + year +
  population_aged_14_to_24_rate + miles_driven_per_capita +
  unemployment_rate + speed_limit_70_plus + per_se_law +
  seat_belt_law + graduated_drivers_license_law,
  data = main_p,
  index = c("state", "year"),
  effect = "individual", model = "within")

summary(expanded.within)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = total_fatalities_rate ~ bac + year + population_aged_14_to_24_rate +
##     miles_driven_per_capita + unemployment_rate + speed_limit_70_plus +
##     per_se_law + seat_belt_law + graduated_drivers_license_law,
##     data = main_p, effect = "individual", model = "within", index = c("state",
##     "year"))
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##      Min.   1st Qu.   Median   3rd Qu.   Max.
## -8.373709 -1.032816 -0.008787  0.964794 14.852853
##
## Coefficients:
##              Estimate Std. Error t-value Pr(>|t|)
## bac10             -9.8836e-01  2.6017e-01  -3.7989 0.0001532 ***
## bac8              -1.4029e+00  3.7457e-01  -3.7454 0.0001893 ***
## year1981          -1.5125e+00  4.1380e-01  -3.6551 0.0002690 ***
```

```

## year1982          -3.0274e+00  4.4324e-01  -6.8302  1.390e-11 ***
## year1983          -3.5378e+00  4.5902e-01  -7.7073  2.826e-14 ***
## year1984          -4.3083e+00  4.6578e-01  -9.2497 < 2.2e-16 ***
## year1985          -4.7868e+00  4.8519e-01  -9.8657 < 2.2e-16 ***
## year1986          -3.7125e+00  5.1746e-01  -7.1744  1.319e-12 ***
## year1987          -4.3587e+00  5.5515e-01  -7.8513  9.599e-15 ***
## year1988          -4.8390e+00  6.0130e-01  -8.0475  2.144e-15 ***
## year1989          -6.1897e+00  6.4022e-01  -9.6681 < 2.2e-16 ***
## year1990          -6.3062e+00  6.6468e-01  -9.4876 < 2.2e-16 ***
## year1991          -6.9736e+00  6.8226e-01 -10.2213 < 2.2e-16 ***
## year1992          -7.8350e+00  7.0308e-01 -11.1439 < 2.2e-16 ***
## year1993          -8.1648e+00  7.1612e-01 -11.4015 < 2.2e-16 ***
## year1994          -8.6022e+00  7.3355e-01 -11.7267 < 2.2e-16 ***
## year1995          -8.3268e+00  7.5599e-01 -11.0144 < 2.2e-16 ***
## year1996          -8.6862e+00  7.9741e-01 -10.8930 < 2.2e-16 ***
## year1997          -8.7995e+00  8.1608e-01 -10.7826 < 2.2e-16 ***
## year1998          -9.4357e+00  8.3257e-01 -11.3332 < 2.2e-16 ***
## year1999          -9.5676e+00  8.4192e-01 -11.3640 < 2.2e-16 ***
## year2000          -1.0086e+01  8.5381e-01 -11.8127 < 2.2e-16 ***
## year2001          -9.7406e+00  8.6850e-01 -11.2154 < 2.2e-16 ***
## year2002          -9.0017e+00  8.7733e-01 -10.2603 < 2.2e-16 ***
## year2003          -9.0439e+00  8.8211e-01 -10.2526 < 2.2e-16 ***
## year2004          -9.4110e+00  9.0453e-01 -10.4044 < 2.2e-16 ***
## population_aged_14_to_24_rate  1.9161e-01  9.5127e-02   2.0143  0.0442176 *
## miles_driven_per_capita        9.3803e-04  1.1114e-04   8.4400 < 2.2e-16 ***
## unemployment_rate             -5.7831e-01  6.0571e-02  -9.5477 < 2.2e-16 ***
## speed_limit_70_plus            -5.2921e-02  2.6059e-01  -0.2031  0.8391103
## per_se_low1                   -1.0602e+00  2.2417e-01  -4.7295  2.538e-06 ***
## seat_belt_lowsecondary         -3.7090e-01  2.5227e-01  -1.4703  0.1417723
## seat_belt_lowprimary           -1.2396e+00  3.4323e-01  -3.6116  0.0003178 ***
## graduated_drivers_license_low -4.0171e-01  2.9266e-01  -1.3726  0.1701493
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    12134
## Residual Sum of Squares: 4548.1
## R-Squared:              0.62518
## Adj. R-Squared: 0.59802
## F-statistic: 54.846 on 34 and 1118 DF, p-value: < 2.22e-16

```

## 5.1 Interpretation of model

### 5.1.1 What do you estimate for coefficients on the blood alcohol variables? How do the coefficients on the blood alcohol variables change, if at all?

We also note that bac value of 0.1% and 0.08% are both statistically significant parameters.

- This model suggests that setting a blood alcohol limit of 0.1% is associated with a 0.99 unit decrease in fatality rate as compared to no BAC limit. Compared to the OLS model which showed that setting a blood alcohol limit of 0.1% is associated with a 1.34 unit decrease in fatality rate as compared to no BAC limit.
- This model suggests that a setting a blood alcohol limit of 0.08% is associated with a 1.4 unit decrease in fatality rate as compared to no BAC limit. Compared to the OLS model which showed that setting

a blood alcohol limit of 0.08% is associated with a 1.4 unit decrease in fatality rate as compared to no BAC limit.

**5.1.2 What do you estimate for coefficients on per se laws? How do the coefficients on per se laws change, if at all?**

We note that per-se law is a statistically significant parameter. This model suggests that having a per-se law is associated with a 1.06 unit decrease in fatality rate as compared to not having per-se law. Compared to the OLS model which showed that having a per-se law is associated with a 0.64 unit decrease in fatality rate as compared to not having per-se law

**5.1.3 What do you estimate for coefficients on primary seat-belt laws? How do the coefficients on primary seatbelt laws change, if at all?**

In this model we note that seat belt primary law is a significant factor. This model suggests that having a primary seat belt law is associated with a 1.24 unit decrease in fatality rate as compared to not having primary seat belt law.

## 6 (10 points) Consider a Random Effects Model

Instead of estimating a fixed effects model, should you have estimated a random effects model?

- Please state the assumptions of a random effects model, and evaluate whether these assumptions are met in the data.
- If the assumptions are, in fact, met in the data, then estimate a random effects model and interpret the coefficients of this model. Comment on how, if at all, the estimates from this model have changed compared to the fixed effects model.
- If the assumptions are **not** met, then do not estimate the data. But, also comment on what the consequences would be if you were to *inappropriately* estimate a random effects model. Would your coefficient estimates be biased or not? Would your standard error estimates be biased or not? Or, would there be some other problem that might arise?

## 7 (10 points) Model Forecasts

The COVID-19 pandemic dramatically changed patterns of driving. Find data (and include this data in your analysis, here) that includes some measure of vehicle miles driven in the US. Your data should at least cover the period from January 2018 to as current as possible. With this data, produce the following statements:

- Comparing monthly miles driven in 2018 to the same months during the pandemic:
  - What month demonstrated the largest decrease in driving? How much, in percentage terms, lower was this driving?
  - What month demonstrated the largest increase in driving? How much, in percentage terms, higher was this driving?

Now, use these changes in driving to make forecasts from your models.

- Suppose that the number of miles driven per capita, increased by as much as the COVID boom. Using the FE estimates, what would the consequences be on the number of traffic fatalities? Please interpret the estimate.



- Suppose that the number of miles driven per capita, decreased by as much as the COVID bust. Using the FE estimates, what would the consequences be on the number of traffic fatalities? Please interpret the estimate.

## 8 (5 points) Evaluate Error

If there were serial correlation or heteroskedasticity in the idiosyncratic errors of the model, what would be the consequences on the estimators and their standard errors? Is there any serial correlation or heteroskedasticity?