10 Case Study II: Drunk Driving

```
library(AER) # for the dataset
library(plm) # panel models
library(stargazer) # regression tables
```

The dataset `Fatalities` contains panel data for traffic fatalities in the United States. Among others, it contains variables related to traffic fatalities and alcohol, including the number of traffic fatalities, the type of drunk driving laws and the tax on beer, reporting their values for each state and each year.

Here we will study how effective various government policies designed to discourage drunk driving actually are in reducing traffic deaths.

The measure of traffic deaths we use is the fatality rate, which is the annual number of traffic fatalities per 10000 individuals within the state's population. The measure of alcohol taxes we use is the "real" tax on a case of beer, which is the beer tax, put into 1988 dollars by adjusting for inflation.

Let's take a look at the structure of the dataset first.

```
data(Fatalities, package = "AER")
class(Fatalities)
```

```
[1] "data.frame"
```

```
dim(Fatalities)
```

```
[1] 336  34
```

```
str(Fatalities)
```

Click here to view or hide `str(Fatalities)`

```
'data.frame':	336 obs. of  34 variables:
 $ state       : Factor w/ 48 levels "al","az","ar",..: 1 1 1 1 1 1 1 2 2 2 ...
 $ year        : Factor w/ 7 levels "1982","1983",..: 1 2 3 4 5 6 7 1 2 3 ...
 $ spirits     : num  1.37 1.36 1.32 1.28 1.23 ...
 $ unemp       : num  14.4 13.7 11.1 8.9 9.8 ...
 $ income      : num  10544 10733 11109 11333 11662 ...
 $ emppop      : num  50.7 52.1 54.2 55.3 56.5 ...
 $ beertax     : num  1.54 1.79 1.71 1.65 1.61 ...
 $ baptist     : num  30.4 30.3 30.3 30.3 30.3 ...
 $ mormon      : num  0.328 0.343 0.359 0.376 0.393 ...
 $ drinkage    : num  19 19 19 19.7 21 ...
 $ dry         : num  25 23 24 23.6 23.5 ...
 $ youngdrivers: num  0.212 0.211 0.211 0.211 0.213 ...
 $ miles       : num  7234 7836 8263 8727 8953 ...
 $ breath      : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ jail        : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 2 2 2 ...
 $ service     : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 2 2 2 ...
 $ fatal       : int  839 930 932 882 1081 1110 1023 724 675 869 ...
 $ nfatal      : int  146 154 165 146 172 181 139 131 112 149 ...
 $ sfatal      : int  99 98 94 98 119 114 89 76 60 81 ...
 $ fatal1517   : int  53 71 49 66 82 94 66 40 40 51 ...
 $ nfatal1517  : int  9 8 7 9 10 11 8 7 7 8 ...
 $ fatal1820   : int  99 108 103 100 120 127 105 81 83 118 ...
 $ nfatal1820  : int  34 26 25 23 23 31 24 16 19 34 ...
 $ fatal2124   : int  120 124 118 114 119 138 123 96 80 123 ...
 $ nfatal2124  : int  32 35 34 45 29 30 25 36 17 33 ...
 $ afatal      : num  309 342 305 277 361 ...
 $ pop         : num  3942002 3960008 3988992 4021008 4049994 ...
 $ pop1517     : num  209000 202000 197000 195000 204000 ...
 $ pop1820     : num  221553 219125 216724 214349 212000 ...
 $ pop2124     : num  290000 290000 288000 284000 263000 ...
 $ milestot    : num  28516 31032 32961 35091 36259 ...
 $ unempus     : num  9.7 9.6 7.5 7.2 7 ...
 $ emppopus    : num  57.8 57.9 59.5 60.1 60.7 ...
 $ gsp         : num  -0.0221 0.0466 0.0628 0.0275 0.0321 ...
```

We can see the data has been effectively defined as a data frame, with 336 observations of 34 variables. Our panel index variables are `state` (individual, i) and `year` (time, t).

It's always good to have a quick look at the first few observations. The `head()` function in R, by default, shows the first six observations (rows) of a data frame or data set. However, you can specify a different number of rows to display by providing the desired count as an argument to the function if needed, like `head(your_data_frame, n = 10)` to display the first 10 rows.

Click here to view or hide `head(Fatalities)`

```
# list the first few observations
head(Fatalities)
```

```
  state year spirits unemp   income   emppop  beertax baptist  mormon drinkage
1    al 1982    1.37  14.4 10544.15 50.69204 1.539379 30.3557 0.32829    19.00
2    al 1983    1.36  13.7 10732.80 52.14703 1.788991 30.3336 0.34341    19.00
3    al 1984    1.32  11.1 11108.79 54.16809 1.714286 30.3115 0.35924    19.00
4    al 1985    1.28   8.9 11332.63 55.27114 1.652542 30.2895 0.37579    19.67
5    al 1986    1.23   9.8 11661.51 56.51450 1.609907 30.2674 0.39311    21.00
6    al 1987    1.18   7.8 11944.00 57.50988 1.560000 30.2453 0.41123    21.00
      dry youngdrivers    miles breath jail service fatal nfatal sfatal
1 25.0063     0.211572 7233.887     no   no      no   839    146     99
2 22.9942     0.210768 7836.348     no   no      no   930    154     98
3 24.0426     0.211484 8262.990     no   no      no   932    165     94
4 23.6339     0.211140 8726.917     no   no      no   882    146     98
5 23.4647     0.213400 8952.854     no   no      no  1081    172    119
6 23.7924     0.215527 9166.302     no   no      no  1110    181    114
  fatal1517 nfatal1517 fatal1820 nfatal1820 fatal2124 nfatal2124  afatal
1        53          9        99         34       120         32 309.438
2        71          8       108         26       124         35 341.834
3        49          7       103         25       118         34 304.872
4        66          9       100         23       114         45 276.742
5        82         10       120         23       119         29 360.716
6        94         11       127         31       138         30 368.421
      pop  pop1517  pop1820  pop2124 milestot unempus emppopus         gsp
1 3942002 208999.6 221553.4 290000.1    28516     9.7     57.8 -0.02212476
2 3960008 202000.1 219125.5 290000.2    31032     9.6     57.9  0.04655825
3 3988992 197000.0 216724.1 288000.2    32961     7.5     59.5  0.06279784
4 4021008 194999.7 214349.0 284000.3    35091     7.2     60.1  0.02748997
5 4049994 203999.9 212000.0 263000.3    36259     7.0     60.7  0.03214295
6 4082999 204999.8 208998.5 258999.8    37426     6.2     61.5  0.04897637
```

```r
# summarize the variables 'state' and 'year'
summary(Fatalities[, c("state", "year")])
```

```
     state        year
 al      :  7   1982:48
 az      :  7   1983:48
 ar      :  7   1984:48
 ca      :  7   1985:48
 co      :  7   1986:48
 ct      :  7   1987:48
 (Other):294   1988:48
```

Notice that the variable `state` is a factor variable with 48 levels (one for each of the 48 contiguous federal states of the U.S.). The variable `year` is also a factor variable that has 7 levels identifying the time period when the observation was made. This gives us $7 \times 48 = 336$ observations in total.

Since all variables are observed for all entities (states) and over all time periods, the panel is *balanced*. If there were missing data for at least one entity in at least one time period we would call the panel *unbalanced*.

10.1 Cross-sectional Regression

Let's start by estimating simple regressions using data for years 1982 and 1988 that model the relationship between the beer tax (adjusted for 1988 dollars) and the traffic fatality rate, measured as the number of fatalities per 10000 inhabitants. Afterwards, we plot the data and add the corresponding estimated regression functions.

```r
# define the fatality rate
Fatalities$fatal_rate = Fatalities$fatal / Fatalities$pop * 10000

# subset the data
Fatalities1982 = Fatalities |> subset(year == "1982")
Fatalities1988 = Fatalities |> subset(year == "1988")

# estimate simple regression models using 1982 and 1988 data
fatal1982_mod = lm(fatal_rate ~ beertax, data = Fatalities1982)
fatal1988_mod = lm(fatal_rate ~ beertax, data = Fatalities1988)

coeftest(fatal1982_mod, vcov. = vcovHC)
```

```
t test of coefficients:

            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.01038    0.15278 13.1586   <2e-16 ***
beertax      0.14846    0.14500  1.0238   0.3113
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
coeftest(fatal1988_mod, vcov. = vcovHC)
```

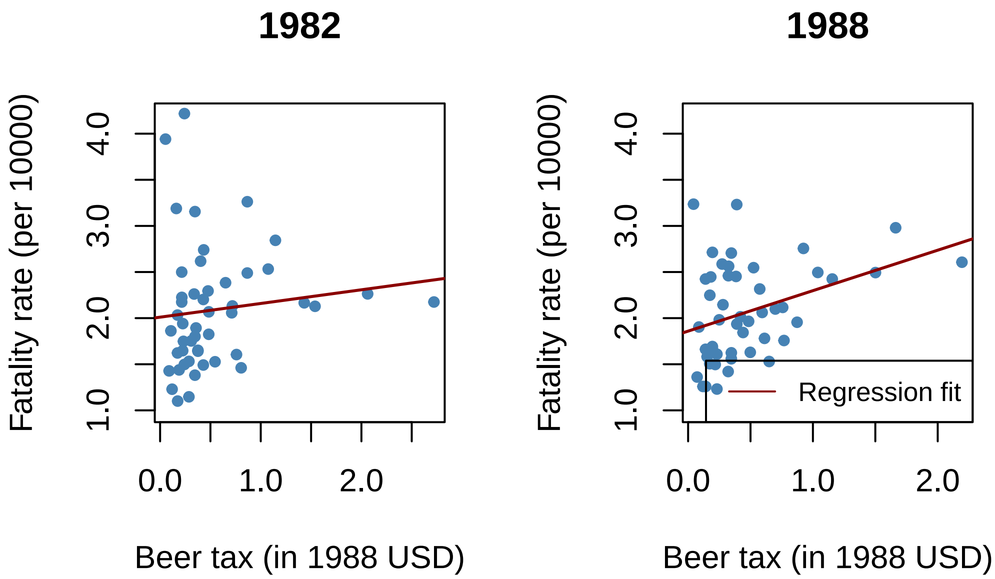
```
t test of coefficients:

            Estimate Std. Error t value  Pr(>|t|)
(Intercept)  1.85907    0.11786 15.7731 < 2.2e-16 ***
beertax      0.43875    0.14224  3.0847  0.003443 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The estimated regression functions are

$$\widehat{FatalityRate} = \underset{(0.15)}{2.01} + \underset{(0.15)}{0.15}\, BeerTax \quad \text{(1982 data)}$$

$$\widehat{FatalityRate} = \underset{(0.12)}{1.86} + \underset{(0.14)}{0.44}\, BeerTax \quad \text{(1988 data)}$$

```r
par(mfrow = c(1,2))
plot(fatal_rate~beertax, data = Fatalities1982,
     xlab = "Beer tax (in 1988 USD)", ylab = "Fatality rate (per 10000)",
     main = "1982", ylim = c(1, 4.2),
     pch = 20, col = "steelblue")
abline(fatal1982_mod, lwd = 1.5, col="darkred")
plot(fatal_rate~beertax, data = Fatalities1988,
     xlab = "Beer tax (in 1988 USD)", ylab = "Fatality rate (per 10000)",
     main = "1988", ylim = c(1, 4.2),
     pch = 20, col = "steelblue")
abline(fatal1988_mod, lwd = 1.5, col="darkred")
legend("bottomright",lty=1,col="darkred","Regression fit", cex = 0.8)
```



In both plots, each point represents observations of beer tax and fatality rate for a given state in the respective year. The regression results indicate a positive relationship between the beer tax and the fatality rate for both years.

The estimated coefficient on beer tax for the 1988 data is almost three times as large as for the 1982 dataset. This is contrary to our expectations: alcohol taxes are supposed to lower the rate of traffic fatalities. This is possibly due to omitted variable bias, since none of the models include any covariates, e.g., economic conditions.

Panel data methods could help here to account for omitted unobservable factors that vary from state to state but can be assumed to be constant over the observation period (e.g., attitudes toward drunk driving, road quality, density of cars on the road) and factors that vary from year to year but can be assumed to be constant for all states in a given year (e.g., changing national attitudes toward drunk driving, improvements in car safety over time).

10.2 "Before and After" Comparisons

Let's suppose there are only $T = 2$ time periods $t = 1982, 1988$. This allows us to analyze differences in changes of the fatality rate from year 1982 to 1988. We start by considering the population regression model:

$$\text{FatalityRate}_{it} = \beta_0 + \beta_1 \text{BeerTax}_{it} + \beta_2 Z_i + u_{it}$$

where the Z_i are state specific characteristics that differ between states but are constant over time. For $t = 1982$ and $t = 1988$ we have

$$FatalityRate_{i,1982} = \beta_0 + \beta_1 \text{BeerTax}_{i,1982} + \beta_2 Z_i + u_{i,1982},$$
$$FatalityRate_{i,1988} = \beta_0 + \beta_1 \text{BeerTax}_{i,1988} + \beta_2 Z_i + u_{i,1988}.$$

We can eliminate the Z_i by regressing the difference in the fatality rate between 1988 and 1982 on the difference in beer tax between those years:

$$\begin{aligned} &\text{FatalityRate}_{i,1988} - \text{FatalityRate}_{i,1982} \\ &= \beta_1(\text{BeerTax}_{i,1988} - \text{BeerTax}_{i,1982}) + u_{i,1988} - u_{i,1982} \end{aligned}$$

This regression model, where the difference in fatality rate between 1988 and 1982 is regressed on the difference in beer tax between those years, yields an estimate for β_1 that is robust to a possible bias due to omission of Z_i, as these influences are eliminated from the model. Next we will estimate a regression based on the differenced data and plot the estimated regression function.

```
# compute the differences
diff_fatal_rate = Fatalities1988$fatal_rate - Fatalities1982$fatal_rate
diff_beertax = Fatalities1988$beertax - Fatalities1982$beertax

# estimate a regression using differenced data
fatal_diff_mod = lm(diff_fatal_rate ~ diff_beertax)
coeftest(fatal_diff_mod, vcov = vcovHC)
```

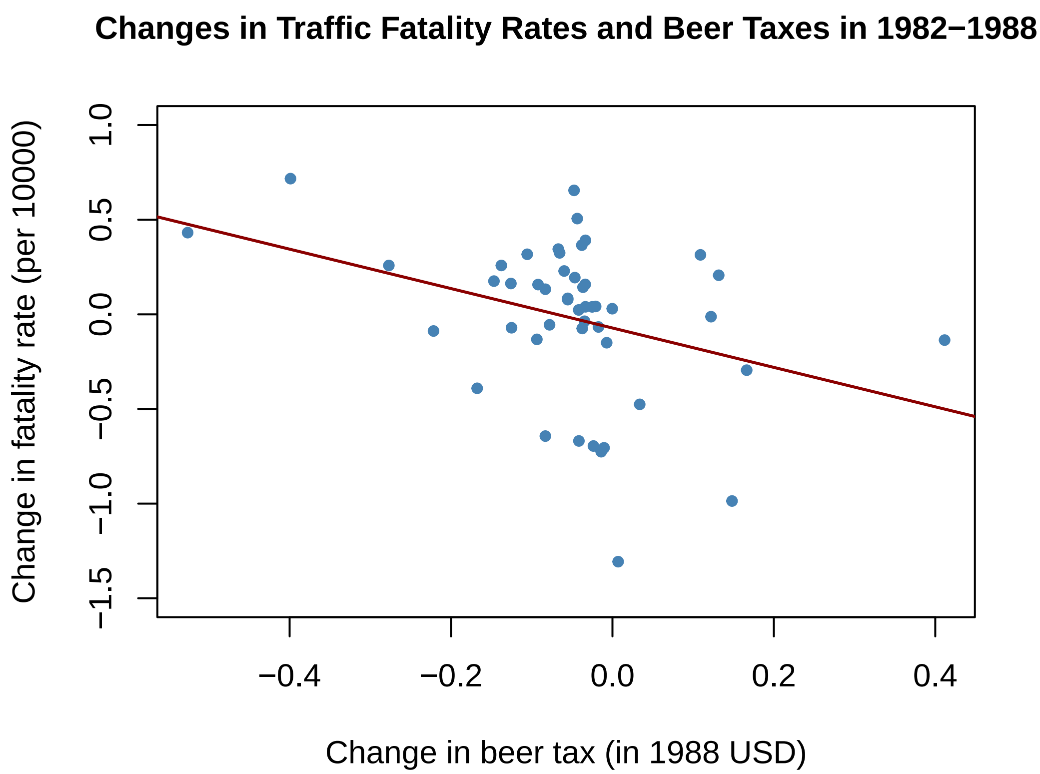
```
t test of coefficients:

              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.072037   0.067854 -1.0616  0.29394
diff_beertax -1.040973   0.408288 -2.5496  0.01418 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Including the intercept allows for a change in the mean fatality rate in the time between 1982 and 1988 in the absence of a change in the beer tax.

We obtain the OLS estimated regression function

$$\widehat{FatalityRate_{i,1988} - FatalityRate_{i,1982}}$$
$$= \underset{(-0.07)}{-0.072} - \underset{(0.41)}{1.04} \left(BeerTax_{i,1988} - BeerTax_{i,1982}\right)$$

```
plot(diff_fatal_rate ~ diff_beertax,
     xlab = "Change in beer tax (in 1988 USD)",
     ylab = "Change in fatality rate (per 10000)",
     main = "Changes in Traffic Fatality Rates and Beer Taxes in 1982-1988",
     ylim = c(-1.5, 1), cex.main=1,
     pch = 20, col = "steelblue")
abline(fatal_diff_mod, lwd = 1.5,col="darkred") # add the regression line to plot
```



The estimated coefficient on beer tax is now negative and significantly different from zero at the 5% significance level. Its interpretation is that raising the beer tax by $1 is associated with an average decrease of 1.04 fatalities per 10000 inhabitants. This is rather large as the average fatality rate is approximately 2 persons per 10000 inhabitants.

```r
# mean fatality rate over all states and time periods
mean(Fatalities$fatal_rate)
```

```
[1] 2.040444
```

The outcome we obtained is likely to be a consequence of omitting factors in the single-year regression that influence the fatality rate and are correlated with the beer tax and change over time. The message is that we need to be more careful and control for such factors before drawing conclusions about the effect of a raise in beer taxes.

The approach presented in this section discards information for years 1983 to 1987. The fixed effects method allows us to use data for more than $T = 2$ time periods and enables us to add control variables to the analysis.

10.3 State Fixed Effects

To estimate the relation between traffic fatality rates and beer taxes, the simple fixed effects model is

$$FatalityRate_{it} = \alpha_i + \beta_1 BeerTax_{it} + u_{it} \tag{10.1}$$

a regression of the traffic fatality rate on beer tax and 48 binary regressors (one for each federal state). In this model, we are using a fixed effects approach to account for the effect of each federal state. α_i represents the state fixed effect. Including a fixed effect for each state means that we're estimating separate intercepts (or constant terms) for each state.

```r
fatal_fe = plm(fatal_rate ~ beertax,
               index = c("state", "year"),
               effect = "individual",
               model = "within",
               data = Fatalities)
coeftest(fatal_fe, vcov. = vcovHC)
```

```

t test of coefficients:

        Estimate Std. Error t value Pr(>|t|)
beertax -0.65587    0.28837 -2.2744  0.02368 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The estimated coefficient is again -0.6559. The estimated regression function is

$$\widehat{FatalityRate} = \underset{(0.29)}{-0.66}\, BeerTax + StateFE \tag{10.2}$$

The coefficient on $BeerTax$ is negative and statistically significant at the 5% level. Its interpretation is that states with a \$1 higher beer tax have, on average, 0.66 fewer traffic fatalities per 10000 people, given the same state-specific time-constant characteristics.

Although including state fixed effects eliminates the risk of bias due to omitted factors that vary across states but not over time, we suspect that there are other omitted variables that vary over time, making it difficult to interpret the coefficient as a causal effect.

If you prefer the `lm()` function, you can also use the following command:

```
fatal_fe_lm = lm(fatal_rate ~ beertax + factor(state) - 1, data = Fatalities)
```

The `-1` term tells R to exclude the intercept term that it would normally include by default. By doing this, we're essentially saying that we don't want to estimate an overall intercept for the model because we are already capturing the state-specific effects. This is a common practice in fixed effects models to avoid multicollinearity between the state-specific intercepts and the predictors.

While `fatal_fe_lm` and `fatal_fe` return the same coefficient estimate, `vcovHC(fatal_fe_lm)` returns the HC3 heteroskedasticity-robust covariance matrix and `vcovHC(fatal_fe)` returns the cluster-robust covariance matrix. The reason is that `fatal_fe_lm` is an `lm` object and `fatal_fe` is a `plm` object. Cluster-robust standard errors should be preferred due to the autocorrelation structure within each cluster (state).

10.4 Year Fixed Effects

Controlling for variables that are constant across entities but vary over time can be done by including time fixed effects. If there are *only* time fixed effects, the fixed effects regression model becomes

$$Y_{it} = \lambda_t + \beta_1 X_{it} + u_{it}$$

In some applications it is meaningful to include both entity (state) and time fixed effects. The **two-way fixed effects model** is

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 X_{it} + u_{it}$$

The combined model allows to eliminate bias from unobservables that change over time but are constant over entities and it controls for factors that differ across entities but are constant over time.

Let's estimate the combined entity and time fixed effects model of the relation between fatalities and beer tax,

$$FatalityRate_{it} = \beta_1 BeerTax_{it} + StateFE_i + TimeFE_t + u_{it}$$

```r
fatal_twoway = plm(fatal_rate ~ beertax,
                   index = c("state", "year"),
                   effect = "twoways",
                   model = "within",
                   data = Fatalities)
coeftest(fatal_twoway, vcov. = vcovHC)
```

```

t test of coefficients:

        Estimate Std. Error t value Pr(>|t|)
beertax -0.63998    0.34963 -1.8305  0.06824 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The estimated regression function is

$$\widehat{FatalityRate} = -\underset{(0.35)}{0.64}\, BeerTax + StateFE + TimeFE \tag{10.3}$$

The result is close to the estimated coefficient for the regression model including only entity fixed effects, which was -0.66. Unsurprisingly, the coefficient is less precisely estimated, as we observe a slightly higher cluster-robust standard error for this new coefficient of -0.64. Nevertheless, it is still significantly different from zero at the 10% level.

We conclude that the estimated relationship between traffic fatalities and the real beer tax is not affected by omitted variable bias due to factors that are constant either over time or across states.

10.5 Driving Laws and Economic Conditions

There are two major sources of omitted variable bias that are not accounted for by all of the models of the relation between traffic fatalities and beer taxes that we have considered so far: economic conditions and driving laws.

Fortunately, `Fatalities` has data on state-specific legal drinking age (`drinkage`), punishment (`jail`, `service`) and various economic indicators like unemployment rate (`unemp`) and per capita income (`income`). We may use these covariates to extend the preceding analysis.

These covariates are defined as follows:

- `unemp`: a numeric variable stating the state specific unemployment rate.
- `log(income)`: the logarithm of real per capita income (in 1988 dollars).
- `miles`: the state average miles per driver.
- `drinkage`: the state specific minimum legal drinking age.
- `drinkagec`: a discretized version of `drinkage` that classifies states into four categories of minimal drinking age; 18, 19, 20, 21 and older. R denotes this as `[18,19)`, `[19,20)`, `[20,21)` and `[21,22]`. These categories are included as dummy regressors where `[21,22]` is chosen as the reference category.
- `punish`: a dummy variable with levels yes and no that measures if drunk driving is severely punished by mandatory jail time or mandatory community service (first conviction).

First, we define some relevant variables to include in our following regression models:

```
# discretize the minimum legal drinking age
Fatalities$drinkagec = factor(floor(Fatalities$drinkage))

# dummy for mandatory jail or community service
Fatalities$punish = ifelse(
  Fatalities$jail == "yes" | Fatalities$service == "yes",
  "yes", "no")
```

Next, we estimate six regression models using `plm()`.

```
# estimate six models
fat_mod1 = plm(fatal_rate ~ beertax,
               index = c("state", "year"),
               model = "pooling",
               data = Fatalities)

fat_mod2 = plm(fatal_rate ~ beertax,
```

```
               index = c("state", "year"),
               effect = "individual",
               model = "within",
               data = Fatalities)

fat_mod3 = plm(fatal_rate ~ beertax,
               index = c("state", "year"),
               effect = "twoways",
               model = "within",
               data = Fatalities)

fat_mod4 = plm(fatal_rate ~ beertax
               + drinkagec + punish + miles + unemp + log(income),
               index = c("state", "year"),
               effect = "twoways",
               model = "within",
               data = Fatalities)

fat_mod5 = plm(fatal_rate ~ beertax
               + drinkagec + punish + miles,
               index = c("state", "year"),
               effect = "twoways",
               model = "within",
               data = Fatalities)

fat_mod6 = plm(fatal_rate ~ beertax
               + drinkage + punish + miles + unemp + log(income),
               index = c("state", "year"),
               effect = "twoways",
               model = "within",
               data = Fatalities)
```

We use `stargazer()` to generate a comprehensive tabular presentation of the results.

```
# gather clustered standard errors in a list
rob_se = list(sqrt(diag(vcovHC(fat_mod1))),
               sqrt(diag(vcovHC(fat_mod2))),
               sqrt(diag(vcovHC(fat_mod3))),
               sqrt(diag(vcovHC(fat_mod4))),
               sqrt(diag(vcovHC(fat_mod5))),
               sqrt(diag(vcovHC(fat_mod6))))
```

```
stargazer(fat_mod1, fat_mod2, fat_mod3, fat_mod4, fat_mod5, fat_mod6,
          se = rob_se,
          type="latex",
          omit.stat = c("f", "rsq", "adj.rsq"),
          add.lines=list(
            c("State FE","no","yes","yes","yes","yes","yes"),
            c("Year FE","no","no","yes","yes","yes","yes"),
            c("Clustered SE","yes","yes","yes","yes","yes","yes"))
          )
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Do, Aug 22, 2024 - 16:08:58

While columns 2 and 3 recap the results of the regressions of Equation 10.1 and Equation 10.2, column 1 presents an estimate of the coefficient of interest in the naive OLS regression of the fatality rate on beer tax without any fixed effects. There we obtain a positive estimate for the coefficient on beer tax that is likely to be upward biased.

The sign of the estimate changes as we extend the model by both entity and time fixed effects in models 2 and 3. Nonetheless, as discussed before, the magnitudes of both estimates may be too large.

The model specifications 4 to 6 include covariates that shall capture the effect of overall state economic conditions as well as the legal framework. Nevertheless, considering **model 4** as the baseline specification including covariates, we observe **four interesting results**:

1. Including these covariates is not leading to a major reduction of the estimated effect of the beer tax. The coefficient is not significantly different from zero at the 10% level, which means that it is considered imprecise.

2. According to this regression model, the minimum legal drinking age is not associated with an effect on traffic fatalities: none of the three dummy variables are significantly different from zero at any common level of significance. Moreover, an F-Test of the joint hypothesis that all three coefficients are zero does not reject the null hypothesis. The next code chunk shows how to test this hypothesis:

```
# test if legal drinking age has no explanatory power (Wald test)
linearHypothesis(fat_mod4,
                 c("drinkagec19", "drinkagec20", "drinkagec21"),
                 vcov. = vcovHC)
```

```
Linear hypothesis test

Hypothesis:
```

Table 10.1

	Dependent variable:					
	fatal_rate					
	(1)	(2)	(3)	(4)	(5)	(6)
beertax	0.365***	−0.656**	−0.640*	−0.445	−0.690**	−0.456
	(0.118)	(0.288)	(0.350)	(0.288)	(0.342)	(0.298)
drinkagec19				−0.046	−0.065	
				(0.057)	(0.064)	
drinkagec20				0.004	−0.090	
				(0.065)	(0.075)	
drinkagec21				−0.028	0.010	
				(0.068)	(0.080)	
drinkage						−0.002
						(0.021)
punishyes				0.038	0.085	0.039
				(0.100)	(0.108)	(0.100)
miles				0.00001	0.00002*	0.00001
				(0.00001)	(0.00001)	(0.00001)
unemp				−0.063***		−0.063***
				(0.013)		(0.013)
log(income)				1.816***		1.786***
				(0.616)		(0.625)
Constant	1.853***					
	(0.117)					
State FE	no	yes	yes	yes	yes	yes
Year FE	no	no	yes	yes	yes	yes
Clustered SE	yes	yes	yes	yes	yes	yes
Observations	336	336	336	335	335	335
Note:				*p<0.1; **p<0.05; ***p<0.01		

```
drinkagec19 = 0
drinkagec20 = 0
drinkagec21 = 0

Model 1: restricted model
Model 2: fatal_rate ~ beertax + drinkagec + punish + miles + unemp + log(income)

Note: Coefficient covariance matrix supplied.

  Res.Df Df  Chisq Pr(>Chisq)
1    276
2    273  3 1.1345     0.7688
```

3. There is no statistical evidence indicating an association between punishment for first offenders and drunk driving: the corresponding coefficient is not significant at the 10% level.

4. The coefficients on the economic variables representing employment rate and income per capita indicate an statistically significant association between these and traffic fatalities. We can check that the employment rate and income per capita coefficients are jointly significant at the 0.1% level.

```
# test if economic indicators have no explanatory power
linearHypothesis(fat_mod4,
                 c("log(income)", "unemp"),
                 vcov. = vcovHC)
```

```
Linear hypothesis test

Hypothesis:
log(income) = 0
unemp = 0

Model 1: restricted model
Model 2: fatal_rate ~ beertax + drinkagec + punish + miles + unemp + log(income)

Note: Coefficient covariance matrix supplied.

  Res.Df Df  Chisq Pr(>Chisq)
1    275
2    273  2 63.155  1.932e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model 5 omits the economic factors. The result supports the notion that economic indicators should remain in the model as the coefficient on beer tax is sensitive to the inclusion of the latter.

Results for model 6 show that the legal drinking age has little explanatory power and that the coefficient of interest is not sensitive to changes in the functional form of the relation between drinking age and traffic fatalities.

10.6 Summary

We have not found statistical evidence to state that severe punishments and an increase in the minimum drinking age could lead to a reduction of traffic fatalities due to drunk driving.

Nonetheless, there seems to be a negative effect of alcohol taxes on traffic fatalities according to our model estimate. However, this estimate is not precise and cannot be interpreted as the causal effect of interest, as there still may be a bias.

There may be omitted variables that differ across states *and* change over time, and this bias remains even though we use a panel approach that controls for entity specific and time invariant unobservables.

10.7 R-codes

methods-sec10.R

Part IV

D) Big Data Econometrics