10.2 Panel Data with Two Time Periods: “Before and After” Comparisons

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

$$FatalityRate_{it} = \beta_0 + \beta_1 BeerTax_{it} + \beta_2 Z_i + u_{it}$$

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

$$\begin{aligned} FatalityRate_{i1982} &= \beta_0 + \beta_1 BeerTax_{i1982} + \beta_2 Z_i + u_{i1982}, \\ FatalityRate_{i1988} &= \beta_0 + \beta_1 BeerTax_{i1988} + \beta_2 Z_i + u_{i1988}. \end{aligned}$$

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:

$$FatalityRate_{i1988} - FatalityRate_{i1982} = \beta_1 (BeerTax_{i1988} - BeerTax_{i1982}) + u_{i1988} - u_{i1982}.$$

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 use R to estimate a regression based on the differenced data and to 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, type = "HC1")
#>
#> t test of coefficients:
#>
#>                Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  -0.072037   0.065355 -1.1022 0.276091
#> diff_beertax -1.040973   0.355006 -2.9323 0.005229 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

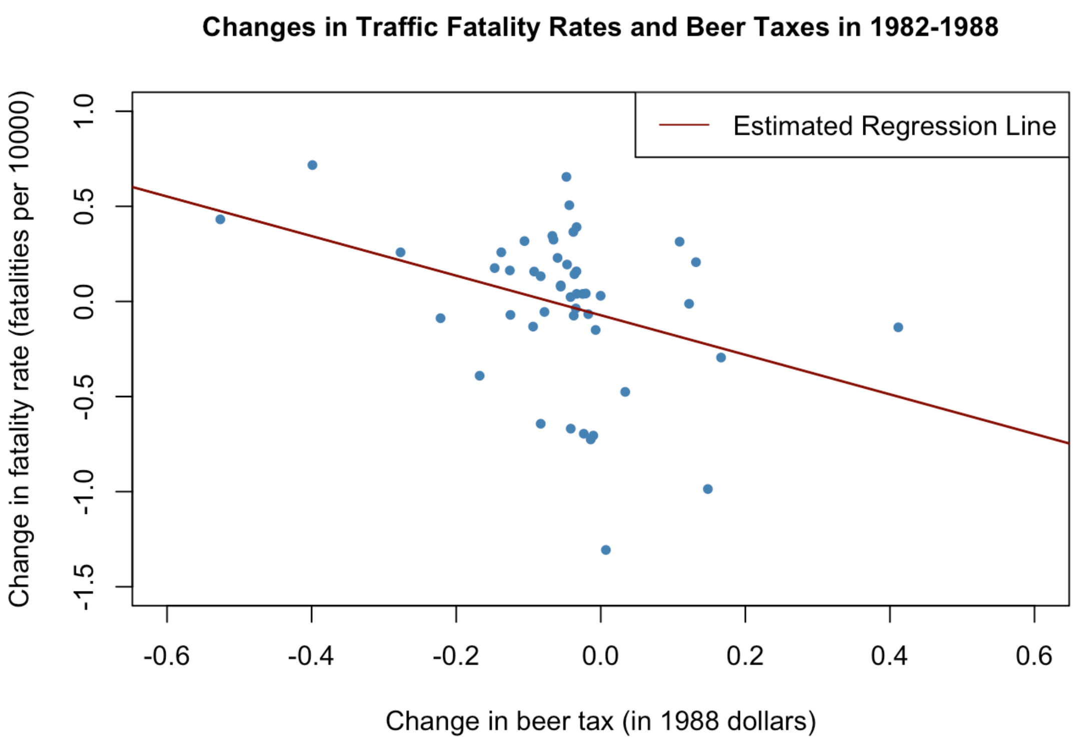
Including the intercept allows for a change in the mean fatality rate in the time between 1982 and 1988 in the absence of a change in the beer tax.

We obtain the OLS estimated regression function

$$\widehat{FatalityRate_{i1988} - FatalityRate_{i1982}} = -\underset{(0.065)}{0.072} - \underset{(0.36)}{1.04} \times (BeerTax_{i1988} - BeerTax_{i1982}).$$

```
# plot the differenced data
plot(x = as.double(diff_beertax),
     y = as.double(diff_fatal_rate),
     xlab = "Change in beer tax (in 1988 dollars)",
     ylab = "Change in fatality rate (fatalities per 10000)",
     main = "Changes in Traffic Fatality Rates and Beer Taxes in 1982-1988",
     cex.main=1,
     xlim = c(-0.6, 0.6),
     ylim = c(-1.5, 1),
     pch = 20,
     col = "steelblue")

# add the regression line to plot
abline(fatal_diff_mod, lwd = 1.5,col="darkred")
#add legend
legend("topright",lty=1,col="darkred","Estimated Regression Line")
```



The estimated coefficient on beer tax is now negative and significantly different from zero at 5%. Its interpretation is that raising the beer tax by $\$1$ causes traffic fatalities to decrease by 1.04 per 10000 people. This is rather large as the average fatality rate is approximately 2 persons per 10000 people.

```
# compute mean fatality rate over all states for all time periods
mean(Fatalities$fatal_rate)
#> [1] 2.040444
```

Once more this outcome 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 that allows us to use data for more than $T = 2$ time periods and enables us to add control variables to the analysis.