Assignment 3: Stevenson & Wolfers QJE 2006

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Summary and Discussion of Stevenson's and Wolfer's Project

Summary

Stevenson and Wolfers investigate the extent to which the passage of laws that increase access to divorce affects the rates of measures of extreme marital distress. They use a difference-in-differences research design, comparing rates of suicide, domestic violence, and spousal homicide before and after the legalization of unilateral divorce.

Their data on suicide come from the National Center for Health Statistics (NCHS) and consist of a complete collection of United States death certificates that identify the cause of death. Their data on domestic violence come from the Family Violence Surveys taken in 1976 and 1985. Their data on homicide come from the FBI Uniform Crime Reports, which provide incident-level information on criminal homicides including data, location, and relationship of the perpetrator to the victim if known.

They find that total female suicide declined in the long run by around 20 percent in states that legalized unilateral divorce. They also find reductions between one percent and five percent in the rates of domestic violence depnding on estimation strategy and direction of violence. They finally find that the rate of intimate homicide decreases, though not significantly.

Discussion

Figure I seems to be the key figure in which they illustrate their main findings. It presents the results for female suicide in a very digestible way without casting doubt on them.

I find the suicide result convincing, particularly its robustness to the battery of alternative estimation procedures as detailed on page 278. However, I worry a little about the accuracy of the suicide data, since those who determined the causes of death for people may have wished to misclassify suicides for religious (or other) reasons. Morever, those motivations may have changed over the course of the decade in which the data was collected as social mores changed.

No-Fault Divorce and the Coase Theorem

No-fault (or *unilateral*) *divorce* is a legal paradigm in which either partner in a marriage may unilaterally carry out divorce proceedings without proving fault-based grounds. Stevenson and Wolfers, citing Gary Becker's 1993 paper "A Treatise on the Family", claim that the Coase theorem implies that no marriage for which the theorem's assumptions hold should persist if either spouse wants a divorce. Thus, Coase's theorem predicts no change in the divorce rate after the passage of a no-fault divorce law. However, Stevenson and Wolfers suggest that spouses that resort to violence likely violate the theorem's assumption of costless bargaining. One would therefore expect to see an increase in the divorce rate among such marriages and a concomitant reduction in the rates of suicide, domestic violence, and spousal homicide.

Explanation of Suicide Estimation Equation

Their estimation equation for state- and time-specific suicide rate is

$$Suicide\,rate_{s,t} = \sum_k \beta_k Unilateral^k_{s,t} + \sum_s \eta_s State_s + \sum_t \lambda_t Year_t + Controls_{s,t} + \varepsilon_{s,t},$$

where

- $Unilateral^k$ is a series of dummy variables set to one for observations that took place in a state that passed a unilateral divorce law k years ago and β_k (the main parameter of interest) is the change in the suicide rate due to that passage;
- $State_s$ is series of dummy variables set to one for observations that took place in a particular state s and η_s is the partial effect of living in that state on suicide rates holding all else fixed;
- $Year_t$ is a series of dummy variables set to one for observations that took place in a particular year t and λ_t is the partial effect of living in that year on suicide rates holding all else fixed;
- $Controls_{s,t}$ is a series of variables meant to control for per-state and per-year differences in demographic and social policies; and
- $\varepsilon_{s,t}$ is the per-state and per-year error term.

The first summation term captures the effect of the unilateral divorce laws. The second and third summation terms capture the state and year fixed effects, respectively.

Table of States and Treatment Dates

```
library(tidyverse)
library(haven)
library(stargazer)
library(knitr)
library(lfe)
library(gridExtra)
library(data.table)
library(bacondecomp)
```

```
# read data
divorce_all <- as.data.table(read_dta("../data/sw_nofault_divorce.dta"))

# drop data not needed for the analysis
divorce <- divorce_all[,1:40]
divorce$region <- divorce_all$region
```

We can see from the table below that five states had not passed no-fault divorce laws by 2006, coded as "NRS": Arkansas, Delaware, Mississippi, New York, and Tennessee. Nine states had passed no-fault divorce laws before 1964, coded as "PRE".

```
# create state, year table
state_timing <- divorce %>%
  group_by(statename) %>%
  summarize(nfd = min(nfd))

state_timing_table = state_timing[1:25,]
state_timing_table[,3:4] = state_timing[26:50,]
state_timing_table[25,3:4] = ''

kable(state_timing_table, col.names = c('State (Column 1)', 'Year',
                                        'State (Column 2)', 'Year'))
```

State (Column 1)	Year	State (Column 2)	Year
Alabama	1971	Nebraska	1972
Arizona	1973	Nevada	1973
Arkansas	NRS	New Hampshire	1971
California	1970	New Jersey	1971
Colorado	1971	New Mexico	1973
Connecticut	1973	New York	NRS
Delaware	NRS	North Carolina	PRE
District of Columbia	1977	North Dakota	1971
Florida	1971	Ohio	1974
Georgia	1973	Oklahoma	PRE
Idaho	1971	Oregon	1973
Illinois	1984	Pennsylvania	1980
Indiana	1973	Rhode Island	1976
Iowa	1970	South Carolina	1969
Kansas	1969	South Dakota	1985
Kentucky	1972	Tennessee	NRS
Louisiana	PRE	Texas	1974
Maine	1973	Utah	PRE
Maryland	PRE	Vermont	PRE
Massachusetts	1975	Virginia	PRE
Michigan	1972	Washington	1973
Minnesota	1974	West Virginia	PRE
Mississippi	NRS	Wisconsin	1977
Missouri	1973	Wyoming	1977
Montana	1975		

Replication

```r
# create post var
divorce$post = 0
divorce[year >= `_nfd`,]$post = 1

# run regressions without trend
homicide_fe_reg = felm(asmrh ~ post |
                         statename + year |
                         0 |
                         statename,
                       data = divorce)
suicide_fe_reg = felm(asmrs ~ post |
                        statename + year |
                        0 |
                        statename,
                      data = divorce)

# create trend var
divorce$trend = divorce$year - 1963

# run regressions with trend
homicide_fe_trend_reg = felm(asmrh ~ post |
                               as.factor(statename):trend + statename + year |
                               0 |
                               statename,
                             data = divorce)
suicide_fe_trend_reg = felm(asmrs ~ post |
                              as.factor(statename):trend + statename + year |
                              0 |
                              statename,
                            data = divorce)
```

```r
# create regression table
stargazer(homicide_fe_reg,
          homicide_fe_trend_reg,
          suicide_fe_reg,
          suicide_fe_trend_reg,
          header = FALSE,
          title = "Simple DD Estimates of Effect of Unilateral Divorce on
          Female ASMR Due to Homicide and Suicide",
          dep.var.labels = c("Homicide", "Suicide"),
          covariate.labels = c("Post-Treatment"),
          add.lines = list(c('State and Year FEs', 'X', 'X', 'X', 'X'),
                           c('State-Specific Trends', ' ', 'X', ' ', 'X')),
          keep.stat = c('n'),
          notes = "Standard errors are clustered by state."
          )
```

Table 2: Simple DD Estimates of Effect of Unilateral Divorce on Female ASMR Due to Homicide and Suicide

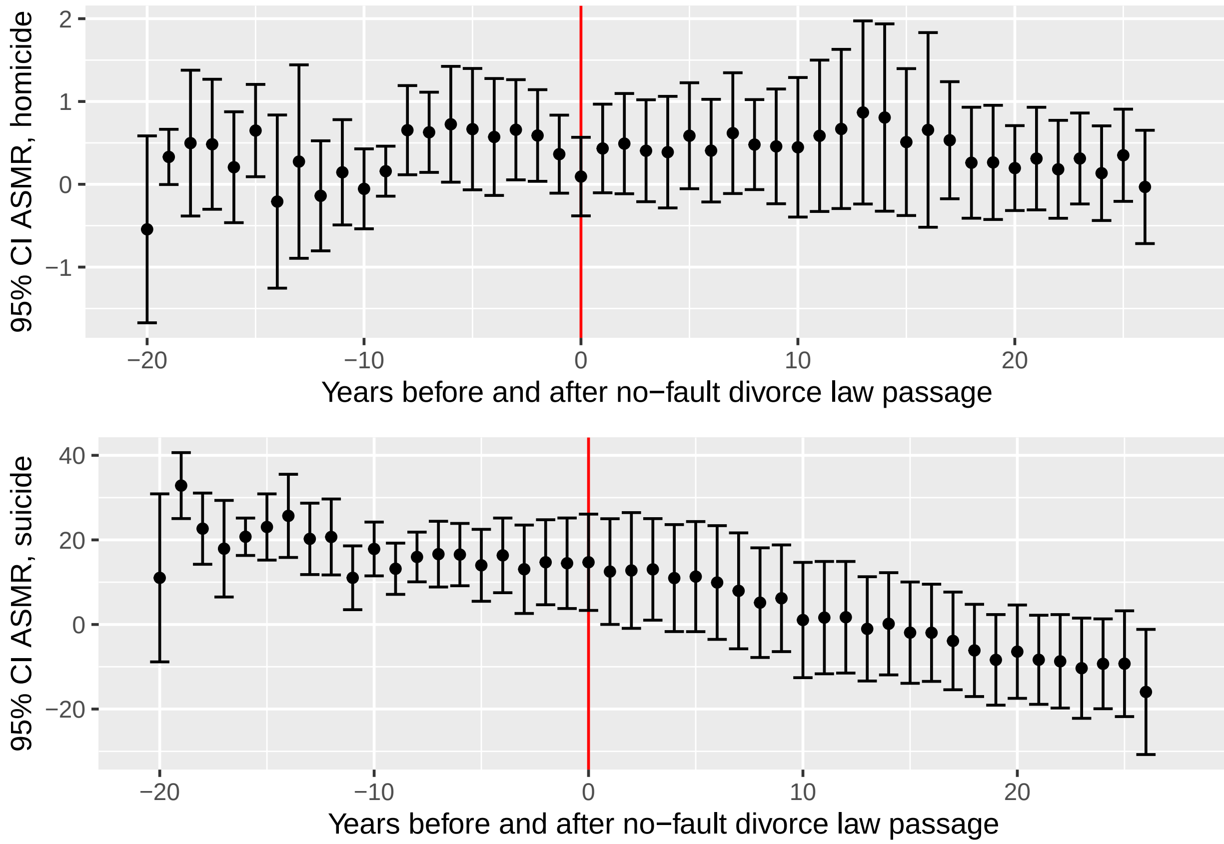
	Dependent variable:			
	Homicide		Suicide	
	(1)	(2)	(3)	(4)
Post-Treatment	−0.150	−0.172	−3.080	0.593
	(0.150)	(0.255)	(2.431)	(2.009)
State and Year FEs	X	X	X	X
State-Specific Trends		X		X
Observations	1,617	1,617	1,617	1,617
Note:		*p<0.1; **p<0.05; ***p<0.01		
		Standard errors are clustered by state.		

Event Study

The identifying assumptions of variance-weighted common trends and time-invariant treatment effects are needed to estimate the variance-weighted ATT using OLS when there is differential timing.

```
# event study

# run regressions with year-distance from treatment
homicide_fe_leadlag_reg = felm(asmrh ~ as.factor(I(year - `_nfd`)) |
                                 statename + year | 0 | statename,
                               data = divorce)
suicide_fe_leadlag_reg = felm(asmrs ~ as.factor(I(year - `_nfd`)) |
                                statename + year | 0 | statename,
                              data = divorce)

# create data for coefficient plot
leadlag_data <- as.data.frame(
  tibble(
    label = -20:27,
    mean_homicide = coef(homicide_fe_leadlag_reg)[1:48],
    se_homicide = homicide_fe_leadlag_reg$cse[1:48],
    mean_suicide = coef(suicide_fe_leadlag_reg)[1:48],
    se_suicide = suicide_fe_leadlag_reg$cse[1:48]
    )
  )

# create homicide coefficient plot
homicide_plot <- ggplot(data = leadlag_data, aes(x = label))+
  geom_vline(xintercept = 0, color = 'red') +
  geom_point(aes(y = mean_homicide)) +
  geom_errorbar(aes(ymin = mean_homicide - 1.96*se_homicide,
                  ymax = mean_homicide +1.96*se_homicide)) +
  xlab("Years before and after no-fault divorce law passage") +
  ylab("95% CI ASMR, homicide")

# create suicide coefficient plot
suicide_plot <- ggplot(data = leadlag_data, aes(x = label)) +
  geom_vline(xintercept = 0, color = 'red') +
```

```r
  geom_point(aes(y = mean_suicide)) +
  geom_errorbar(aes(ymin = mean_suicide - 1.96*se_suicide,
                    ymax = mean_suicide +1.96*se_suicide)) +
  xlab("Years before and after no-fault divorce law passage") +
  ylab("95% CI ASMR, suicide")

# display stacked plots
grid.arrange(homicide_plot, suicide_plot, ncol=1)
```




```r
homicide_fe_leadlag_post_reg = felm(asmrh ~ post + as.factor(I(year - `_nfd`)) | statename + year | 0 |
suicide_fe_leadlag_post_reg = felm(asmrs ~ post + as.factor(I(year - `_nfd`)) | statename + year | 0 | s


stargazer(homicide_fe_leadlag_post_reg,
          suicide_fe_leadlag_post_reg,
          header = FALSE,
          single.row = TRUE,
          model.numbers = FALSE,
          title = "Estimates of Mean Female ASMR Due to Homicide and Suicide in Lead and Lag Years",
          dep.var.caption = '',
          dep.var.labels = c("Homicide", "Suicide"),
          covariate.labels = c("Post-Treatment", "Lead 20", "Lead 19", "Lead 18", "Lead 17", "Lead 16",
          keep.stat = c('n'),
          notes = "Standard errors are clustered by state."
          )
```

Table 3: Estimates of Mean Female ASMR Due to Homicide and Suicide in Lead and Lag Years

	Homicide	Suicide
Post-Treatment	0.165 (0.430)	26.154** (10.329)
Lead 20	−0.541 (0.574)	11.569 (10.111)
Lead 19	0.337* (0.167)	33.934*** (4.135)
Lead 18	0.508 (0.444)	24.293*** (4.407)
Lead 17	0.497 (0.394)	20.101*** (6.002)
Lead 16	0.223 (0.349)	23.466*** (3.067)
Lead 15	0.670** (0.291)	26.323*** (4.958)
Lead 14	−0.185 (0.550)	29.497*** (6.099)
Lead 13	0.302 (0.613)	24.603*** (5.498)
Lead 12	−0.108 (0.388)	25.598*** (5.596)
Lead 11	0.179 (0.357)	16.486*** (5.408)
Lead 10	−0.017 (0.319)	23.850*** (4.917)
Lead 9	0.200 (0.227)	19.718*** (5.131)
Lead 8	0.698** (0.310)	23.046*** (5.328)
Lead 7	0.676** (0.300)	24.263*** (6.394)
Lead 6	0.777** (0.372)	24.699*** (6.586)
Lead 5	0.721* (0.405)	22.709*** (7.495)
Lead 4	0.630 (0.406)	25.605*** (7.953)
Lead 3	0.721* (0.383)	22.869** (9.014)
Lead 2	0.655* (0.363)	25.067*** (9.009)
Lead 1	0.433 (0.397)	25.375** (9.496)
Treatment Year	(0.000)	(0.000)
Lag 1	0.343** (0.154)	−1.657 (1.862)
Lag 2	0.405* (0.219)	−0.851 (2.631)
Lag 3	0.322 (0.243)	−0.051 (2.376)
Lag 4	0.309 (0.286)	−1.562 (2.701)
Lag 5	0.510* (0.300)	−0.666 (2.765)
Lag 6	0.334 (0.260)	−1.520 (3.225)
Lag 7	0.549 (0.358)	−2.943 (3.458)
Lag 8	0.414* (0.230)	−5.194 (3.227)
Lag 9	0.396 (0.330)	−3.612 (3.295)
Lag 10	0.388 (0.417)	−8.212** (3.871)
Lag 11	0.531 (0.469)	−7.098* (3.948)
Lag 12	0.617 (0.502)	−6.466 (4.244)
Lag 13	0.819 (0.568)	−8.666** (3.842)
Lag 14	0.762 (0.591)	−6.920* (3.964)
Lag 15	0.468 (0.448)	−8.469** (4.149)
Lag 16	0.619 (0.607)	−7.959* (4.188)
Lag 17	0.498 (0.360)	−9.336** (4.399)
Lag 18	0.229 (0.320)	−11.041** (4.186)
Lag 19	0.237 (0.342)	−12.730*** (4.336)
Lag 20	0.172 (0.239)	−10.243** (4.757)
Lag 21	0.290 (0.296)	−11.619** (4.591)
Lag 22	0.164 (0.282)	−11.438** (5.065)
Lag 23	0.298 (0.267)	−12.522** (5.708)
Lag 24	0.124 (0.279)	−10.939** (5.292)
Lag 25	0.344 (0.278)	−10.365 (6.349)
Lag 26	−0.035 (0.348)	−16.502** (7.631)
Lag 27	(0.000)	(0.000)
Observations	1,188	1,188

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered by state.

```r
homicide_bacon_decomp <- bacon(asmrh ~ post,
                              data = divorce, id_var = "statename",
                              time_var = "year")
```

```
##                       type  weight  avg_est
## 1 Earlier vs Later Treated 0.11065 -0.38378
## 2 Later vs Earlier Treated 0.26464 -0.11567
## 3     Treated vs Untreated 0.62470 -0.12238
```

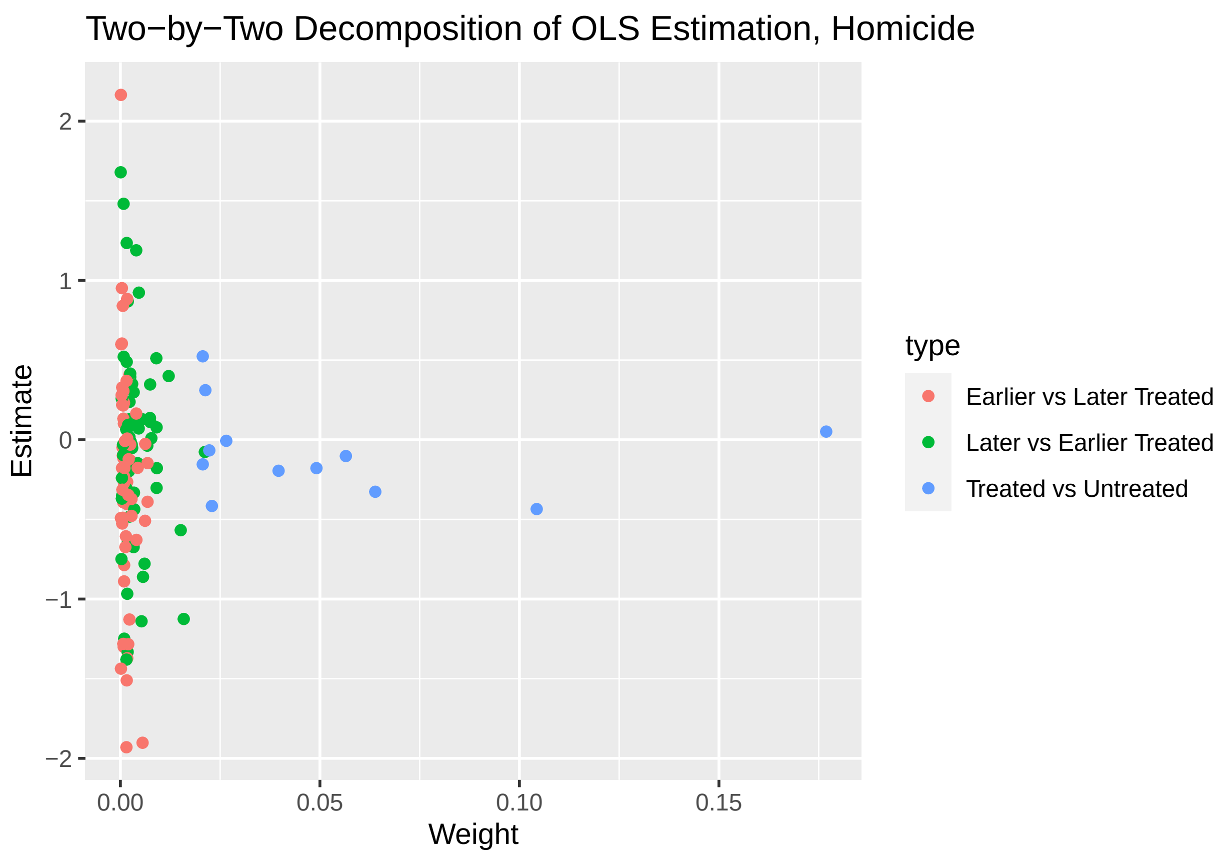
```r
suicide_bacon_decomp <- bacon(asmrs ~ post,
                  data = divorce, id_var = "statename",
                  time_var = "year")
```

```
##                       type  weight  avg_est
## 1 Earlier vs Later Treated 0.11065 -0.18677
## 2 Later vs Earlier Treated 0.26464  3.51197
## 3     Treated vs Untreated 0.62470 -6.38493
```

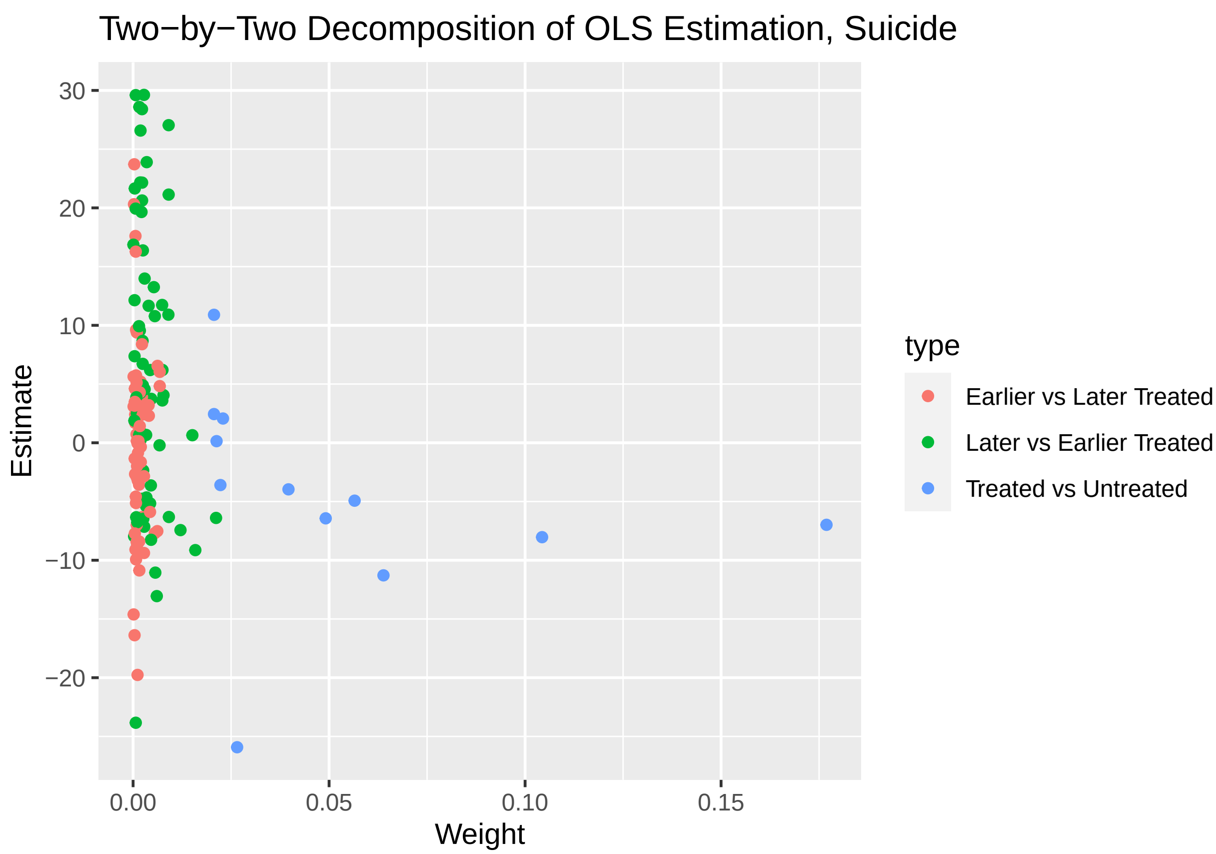
The coefficients on the leads and lags are the mean age-specific mortality rates due to suicide or spousal homicide at year $t - k$ before or after the passage of the laws.

These coefficients are not measured compared to the untreated control units, so they do not convince me that the treatment group units were not statistically different from the control units in the pretreatment period.

```r
homicide_bacon_decomp_plot_data = as.data.frame(homicide_bacon_decomp)
suicide_bacon_decomp_plot_data = as.data.frame(suicide_bacon_decomp)

ggplot(data = homicide_bacon_decomp_plot_data) +
  geom_point(aes(x = weight, y = estimate, color = type)) +
  labs(title ="Two-by-Two Decomposition of OLS Estimation, Homicide") +
  xlab("Weight") +
  ylab("Estimate")
```




```r
ggplot(data = suicide_bacon_decomp_plot_data) +
  geom_point(aes(x = weight, y = estimate, color = type)) +
  labs(title = "Two-by-Two Decomposition of OLS Estimation, Suicide") +
  xlab("Weight") +
  ylab("Estimate")
```




```
sum(homicide_bacon_decomp_plot_data$weight*homicide_bacon_decomp_plot_data$estimate)
```

```
## [1] -0.1495266
```

```
sum(suicide_bacon_decomp_plot_data$weight*suicide_bacon_decomp_plot_data$estimate)
```

```
## [1] -3.079926
```

Note that these sums are identical to the DD coefficients I estimated above.

The static DD parameter is a biased estimate of the true ATT if the treatment effect varies over time or if the variance-weighted common trends do not sum to 0. The former is testable, but the latter is not because it requires knowledge of the counterfactual. We should only be as concerned about this untestability as we are about the untestability of the assumption of parallel trends in the simple two-by-two DD estimator.