Lab #19 - Minimum Wages and Unemployment

Econ 224

November 13th, 2018

Introduction

The following questions are based on a dataset called minwage.dta that you can download from the Mastering 'Metrics website: click on "Instructor's Corner," then scroll down to the bottom of the page. This dataset contains information collected from fast food restaurants in New Jersey and eastern Pennsylvania during two interview waves, the first in March of 1992 and the second in November-December of the same year. Between these two interview waves – on April 1st to be precise – the New Jersey minimum wage increased by just under 19%, from \$4.25 to \$5.05 per hour. The minimum wage in Pennsylvania was unchanged during this period: \$4.25 per hour. The minwage.dta dataset is drawn from a famous but controversial study of the effects of minimum wages by Angrist & Kreuger. The study is so famous that there is even an oblique reference to it on the label of a certain brand of shampoo! (Sadly they do not provide the full citation.) Here is a description of the variables that you will need to carry out this exercise. When you see a pair of variables in the table below, e.g. fte / fte2, both measure the same thing but the one with the 2 is based on the second survey wave, while the one without the 2 is based on the first survey wave.

Name	Description	
state	Dummy variable =1 for NJ, =0 for PA	
wage_st / wage_st2	Starting wage in dollars/hour at the restaurant	
fte / fte2	Full-time equiv. employment = $\#$ (Full time employees) +	
	#(Part-time Employees)/2. Excludes managers.	
chain	Categorical variable taking values in $\{1, 2, 3, 4\}$ to indicate the four	
	chains in the dataset: Burger King, KFC, Roy Rogers, and Wendy's	
co_owned	Dummy variable $=1$ if restaurant is company-owned, $=0$ if	
	franchised	
sample	Dummy variable =1 if wage and employment data are available for	
-	both survey waves at this restaurant	

Exercises

1. Preliminaries:

- (a) Download the data and load it in R using an appropriate package.
- (b) Restrict the sample to only those restaurants with **sample** equal to 1 to ensure that we are making an apples-to-apples comparison throughout the remainder of this lab.
- (c) Rename the column state to treat.
- (d) Create a new column called state that equals PA if treat is 0 and NJ if treat is 1.
- (e) Create a column called low_wage that takes the value 1 if wage_st is less than 5.

2. Baseline Diff-in-Diff Estimate: starting wages

- (a) Calculate the average wage in each survey wave separately for each state.
- (b) Calculate the within-state time-differences based on (a).
- (c) Calculate the between-state difference-in-differences based on (c).
- (d) Interpret your findings from (c). What do they tell us about the causal effect of increasing the minimum wage? What assumptions are required for this interpretation to be valid?

- 3. Baseline Diff-in-Diff Estimate: full time equivalent employment
 - (a) Repeat question 2 but using full-time equivalent employment as the outcome variable rather than starting wages.
- 4. Reshape minwage for Diff-in-Diff Regression Estimation:
 - (a) Create a tibble called wave1 containing only the columns state, treat, wage_st, fte, chain, co_owned, and low_wage. Add a column walled post to wave1 that equals 0 for every observation.
 - (b) Create a tibble called wave2 containing only the columns state, treat, wage_st2, fte2, chain, co_owned, and low_wage. Rename wage_st2 to wage_st and fte2 to fte. Then add a column walled post to wave2 that equals 1 for every observation.
 - (c) Create a tibble called both_waves by *stacking* wave1 on top of wave2. You can do this using the bind_rows command from dplyr. (Read the help file for more details.)
- 5. Diff-in-Diff Regression Estimates:
 - (a) Consider the following regression model using the variables treat and post constructed above:

$$Y_{i,s,t} = \beta_0 + \beta_1(\mathtt{treat}_{i,s}) + \beta_2(\mathtt{post}_t) + \beta_3(\mathtt{treat}_{i,s} \times \mathtt{post}_t) + \epsilon_{i,s,t}$$

where i indexes restaurants, s indexes states, and t indexes $time\ periods$, i.e. the two survey waves. Explain the meaning of each of the four regression coefficients. Which one gives the Regression differences-in-differences effect?

- (b) Estimate the regression from part (a) based on both_waves using wage_st as the outcome variable. Summarize your results, including appropriate statistical inference. How do they compare to those that you calculated in question 2 above?
- (c) Estimate the regression from part (a) based on both_waves using fte as the outcome variable. Summarize your results, including appropriate statistical inference. How do they compare to those that you calculated in question 3 above?
- (d) An advantage of the regression-based formulation of differences-in-differences is that it allows us to control for other variables that might affect wages and employment. Repeat parts (b) and (c) adding co_owned and dummy variables for each of the four restaurant chains to your regression. Hint: rather than creating separate dummy variables from each of the values that chain can take, use as.factor() to convert chain to a factor. Then if you include chain in a regression, R will automatically create the dummy variables for you.
- (e) How do your results from part (d) compare with those of parts (b) and (c)?
- 6. Probing the Diff-in-Diff Assumption:
 - (a) What assumption is required for the diff-in-diff approach to provide a valid causal estimate of the effects of New Jersey raising its minimum wage?
 - (b) An alternative to the comparison of NJ and PA restaurants is a within NJ comparison. The key insight here is that only restaurants with starting wages below \$5 per hour in the first wave will be affected by the change in minimum wages. Use the variable low_wage to run this alternative to the regression from 5(a) using only observations from NJ. Discuss your findings.
 - (c) What assumption is needed for the DD estimate from (b) to be reliable? How plausible is this assumption compared to the assumption from (a)?
 - (d) Repeat part (b) but restrict attention to restaurants in PA where there was no change in minimum wages. Discuss your findings. What do these results suggest about the plausibility of the diff-in-diff assumption in part (b)?

Solutions

```
# 1 - Preliminaries
library(tidyverse)
library(haven)
minwage <- read dta('~/econ224/labs/minwage.dta')</pre>
minwage <- minwage %>% filter(sample == 1) %>%
  rename(treat = state) %>%
  mutate(state = case_when(treat == 0 ~ 'PA',
                           treat == 1 ~ 'NJ'),
         low_wage = 1 * (wage_st < 5))</pre>
# 2 - Baseline Diff-in-Diff: starting wages
DinD_wage <- minwage %>% group_by(state) %>%
  summarize(mean_wage_st = mean(wage_st),
            mean_wage_st2 = mean(wage_st2)) %>%
  mutate(diff = mean_wage_st2 - mean_wage_st)
DinD_wage
# A tibble: 2 x 4
  state mean_wage_st mean_wage_st2
                                      diff
  <chr>
           <dbl>
                                     <dbl>
                        <dbl>
               4.61
                            5.08 0.469
1 NJ
2 PA
                4.65
                             4.62 -0.0348
with(DinD_wage, diff[1] - diff[2])
[1] 0.5040066
# 3 - Baseline Diff-in-Diff: full-time equivalent employment
DinD_emp <- minwage %>% group_by(state) %>%
  summarize(mean_fte = mean(fte),
            mean_fte2 = mean(fte2)) %>%
  mutate(diff = mean_fte2 - mean_fte)
DinD_emp
# A tibble: 2 x 4
  state mean_fte mean_fte2 diff
  <chr> <dbl> <dbl> <dbl>
                     17.6 0.287
1 NJ
           17.3
                     18.1 -2.02
2 PA
           20.1
with(DinD_emp, diff[1] - diff[2])
[1] 2.301994
# 4 - Reshape dataset for Diff-in-Diff regression estimation
wave1 <- minwage %>%
  select(state, treat, wage_st, fte, chain, co_owned, low_wage) %>%
  mutate(post = 0)
wave2 <- minwage %>%
  select(state, treat, wage_st2, fte2, chain, co_owned, low_wage) %>%
```

```
mutate(post = 1) %>%
  rename(wage_st = wage_st2, fte = fte2)
both_waves <- bind_rows(wave1, wave2)</pre>
```

Solution to 5(a)

Blah blah blah...

Table 2:

	Dependent variable:		
	Starting Wage	Full-time Equiv. Employment	
	(1)	(2)	
treat	-0.04	-2.84^{**}	
	(0.04)	(1.22)	
post	-0.03	-2.02	
•	(0.05)	(1.56)	
treat:post	0.50***	2.30	
•	(0.05)	(1.73)	
Constant	4.65***	20.11***	
	(0.03)	(1.10)	
Observations	702	702	
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 3:

	$Dependent\ variable:$	
	Starting Wage (1)	Full-time Equiv. Employment
		(2)
treat	-0.04	-2.14^{*}
	(0.04)	(1.10)
post	-0.03	-2.02
	(0.05)	(1.40)
co owned	0.07***	-1.01
	(0.02)	(0.72)
chain2	0.02	-10.16***
	(0.03)	(0.84)
chain3	0.05	-1.35
	(0.03)	(0.86)
chain4	0.12***	-1.37
	(0.03)	(0.97)
treat:post	0.50***	2.30
•	(0.05)	(1.55)
Constant	4.59***	22.56***
	(0.04)	(1.05)
Observations	702	702

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 4: Within NJ comparison

	Dependent variable:	
	Starting Wage	Full-time Equiv. Employment
	(1)	(2)
low_wage	-0.65***	-2.23*
	(0.02)	(1.21)
post	-0.004	-2.25
	(0.03)	(1.50)
low_wage:post	0.62***	3.30^{*}
	(0.03)	(1.71)
Constant	5.11***	18.99***
	(0.02)	(1.06)
Observations	570	570
\overline{Note} :		*p<0.1; **p<0.05; ***p<0.01

Table 5: Within PA comparison

	D	Dependent variable:	
	Starting Wage (1)	Full-time Equiv. Employmen	
		(2)	
low_wage	-0.63***	-0.89	
	(0.07)	(2.67)	
post	-0.27***	-3.85	
	(0.08)	(3.04)	
low_wage:post	0.35***	2.81	
	(0.10)	(3.77)	
Constant	5.07***	20.70***	
	(0.06)	(2.15)	
Observations	132	132	
37 /		* .0.1 ** .0.0* *** .0.01	

Note:

*p<0.1; **p<0.05; ***p<0.01