Assignment 3

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1. **What is the interpretation of β0, β1, β2 and β3 in the regression?**
   $Grades_i = \beta_0 + \beta_1 Female_i + \beta_2 SmallClass_i + \beta_3 (Female \times SmallClass)_i + u_i$

   If the coefficient is statistically significant, the t-value, beta will give the degree of difference for every 1-unit change in the predictor. Further, the beta value can take on a negative or a positive value. In this case, β_0 is the intercept of the equation. β_1 measures the degree in change of one more unit of the female predictor. β_2 measures the degree in change of one more unit of the small class predictor. β_3 measures the degree in change of one more unit of the interaction term, in this case the interaction term is female x small class.

2. **a) What is the most important assumption needed to make a causal inference in difference- in-difference models?**

   The most important assumption is to claim parallel trends meaning that changes in the treated group would have been the same as in the control group without treatment. Also if the treatment group is randomly assigned, the B_1 coefficient is unbiased and consistent of the causal effect.

   b) How do you check that the assumption hold?

   You need to compare data from two different points; before treatment, and after treatment and then see how the change in the treatment group correlates to how the control group has been behaving. This can be done by comparing two different neighboring municipalities, where one of them goes through a change of some sort. If one of them has a change in health care system, the other municipality can work as the control group. By using these two municipalities' data, you can conduct a study and use the difference in difference model.

3. **Reproduce the results in Table 1 (Descriptive Statistics), Panel A (Men Aged 21-39), column 1 and 2 (1988), for Age through Weeks worked. Show your results in a table. Hint: The descriptive statistics in Table 1 show means.**

Desriptive Statistics - Disabled

	Control Mean
Age	31.49
White	0.823
Post-high school	0.283
Working	0.537
Weeks worked	19.86
Observations	9815

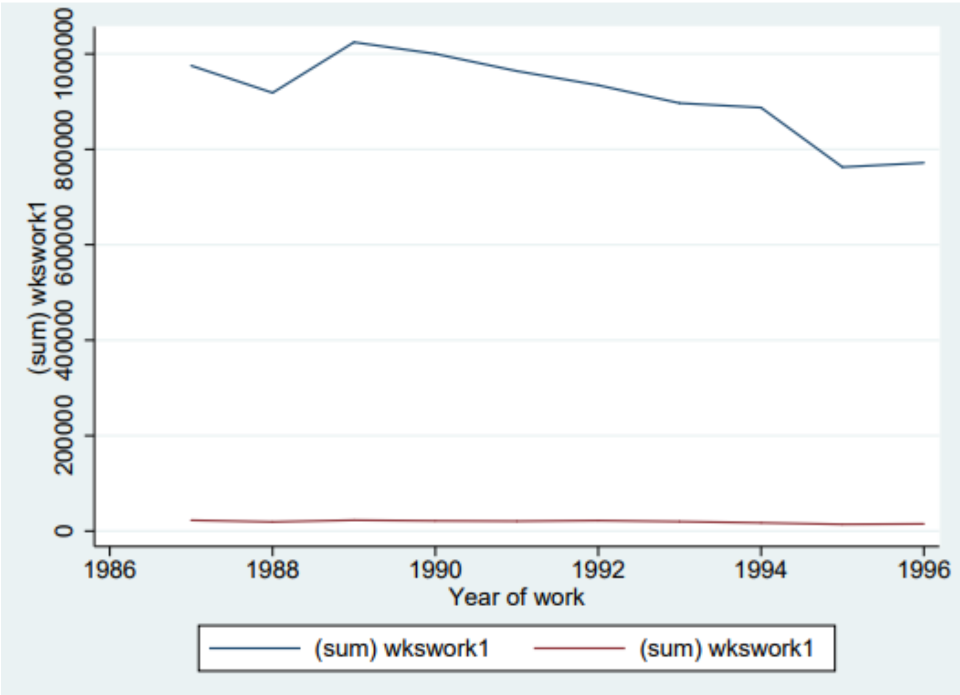
mean coefficients; t statistics in brackets
* p<0.05, ** p<0.01, *** p<0.001

Descriptive Statistics - Non-Disabled

	Control Mean
Age	30.28
White	0.866
Post-high school	0.500
Working	0.950
Weeks worked	44.86
Observations	203652

mean coefficients; t statistics in brackets
* p<0.05, ** p<0.01, *** p<0.001

a) Create a graph with trends in workweeks for the treatment and control groups (Figure 2a, for non-disabled men and disabled men).



4. **Run a regular DD-regression: $Y_{it} = \beta_0 + \beta_1 Disabled_i + \beta_2 After_t + \beta_3(After_t \times Disabled_i) + u_{it}$ Produce a table with your regression output.**

```
--------------------------------
---
                          (1)
                     wkswork1
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---
Disabled              -24.04***
24.04***
                    (-111.57)

ada                   -0.0882
                      (-1.32)

AfterDisab~d          -1.998***
1.998***
                      (-6.41)

_cons                  44.90***
44.90***
                     (983.45)
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N                      213467
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---
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
```

b) Which coefficient is your DD-effect and how do you interpret this effect?

$Y_{it} = \beta_0 + \beta_1 Disabled_i + \beta_2 After_t + \beta_3(After_t \times Disabled_i) + u_{it}$

Mean value of treated (After treated - Before treated) = $(B_0+B_1+B_2+B_3)$ - (B_0+B_1) = B_2+B_3
(Disabled == 1)

Mean value of untreated (After untreated - Before untreated) = (B0+B2) - (B0) = B_2
(Disabled == 0)

DD = Mean value Treated - Mean value Control = $(B_2+B_{3)}$- (B_2) = B_3

The coefficient of the DD-effect is β_3 which is the interaction term and hence the determinant coefficient for the average change in the treatment group and the control group. In other words, it estimates the average effect of weeks being worked when you are disabled and with ADA implemented.

c) Generate a new interaction dummy variable for each year Year × Disabled (as if ADA was implemented in 1988, in 1989, etc.). Run a regression with the new interaction dummy variables, the year dummies, and the Disabled dummy.

$\mathbf{Y_{it} = \beta_0+\beta_1 Disabled_i+{}_{\gamma 88}Dummy88_t+...+{}_{\gamma 96}Dummy97_t+{}_{\lambda 88}(After88_t \times Disabled_i)+ ... + {}_{\lambda 96}(After96_t \times Disabled_i) + u_i}$

Regression with interaction term Year x Disabled

	Weeks worked
dummy=1 if have wo~y	*** [-48.36]
ada88	** [2.80]
ada89	*** [11.68]
ada89	[.]
ada90	*** [8.06]
ada91	[1.47]
ada92	[0.13]
ada93	[1.76]
ada94	*** [4.03]
ada95	*** [7.17]
ada96	*** [8.34]
AfterDisabled88	[-1.21]
AfterDisabled89	[-0.29]
AfterDisabled90	*** [-3.53]
AfterDisabled91	*** [-3.35]
AfterDisabled92	* [-2.26]
AfterDisabled93	*** [-4.24]
AfterDisabled94	*** [-5.01]
AfterDisabled95	*** [-5.67]
AfterDisabled96	*** [-6.18]
Constant	*** [436.45]
Observations	213467

Mean coefficients; t statistics in brackets
* p<0.05, ** p<0.01, *** p<0.001

d) What does the coefficients on treatment for years 1988-1992 show? Given your results, do you think that the result in 4a) from your regular DD-regression can be interpreted causally?

The interaction term shows all negative values (for 1988-1992) meaning that week's worked for disabled people haven't improved because of the ADA. A majority of those are also significant. Compared to the result in 4a) which also shows a negative effect of -1,998 and on a significance level of $p<0.001$ we could conclude that the DD-regression can be causally interpreted.

5. **a) Describe the empirical method with a few sentences. How are control and treatment groups determined? How are before and after years determined?**

   To estimate a causal effect, the study uses Difference-in-difference with panel data and control variables that include family and county characteristics, county transfer income, county fixed effects, year effects and state-specific linear time trends.

   The treatment group is determined whether the county has a food stamp program while the control group does not have any food stamp program introduced. FSP programs were introduced very differently across counties in the US, with the earliest 1961. Depending on when the program was introduced in the specific county observed, this also determined before and after years for that county.

   b) In regression (2) on page 124 $y_{ict} = \alpha + \delta FSP_{ct} + X_{it}\beta + \gamma_1 Z_{c60}t + \gamma_2 TP_{ct} + \eta_c + \delta_t + \lambda_s t + \varepsilon_{ict}$. Which is the coefficient of interest? What does it measure?

   δFSP_{ct} is the coefficient of interest. This variable is a dummy variable that equals one if a county has an FSP program. It measures the effect on food spending depending if a county is in the FSP program and hence receives in kind transfers (here food stamps).