Difference in differences method

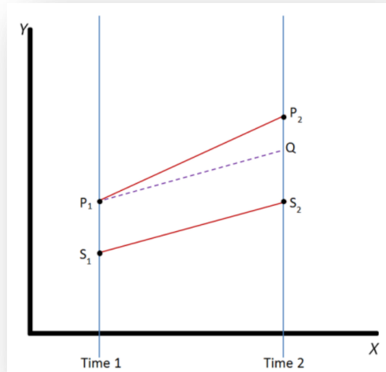
(Summary)

Difference in differences method is a statistical technique used primarily for quantitative research to observe a treatment effect. Generally, to conclude with significant impact of a treatment or a policy two groups should be compared: treatment group and control group. Both groups are assumed to have similar trends in this model. The control group is a group which is kept constant without any changes to observe the expected common trend. The treatment group, on the other hand, is a group to which a treatment or some essential change was applied. Two groups compared, i. e. their differences, give significant results. The panel data, rather than cross section and time series data, is used for this method. Moreover, the difference in differences method is popular in natural experiments.

Among the famous examples is Card and Krueger's paper "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania" (1994), where the minimum wage increase in New Jersey from $4.25 to $5.05 of 1992 was studied. The average employment in fast food sectors of both states with their differences are given in the table below. The difference in differences is 2.75 of average employees per fast food store in this case.

	New Jersey	Pennsylvania	Difference
February	20.44	23.33	−2.89
November	21.03	21.17	−0.14
Change	0.59	−2.16	2.75

The difference in differences can be also observed in the graph below. Since the lower red line is the control group, the higher one, the treatment group, is expected to be parallel if no treatments were applied. The real change can be observed in the graph:



The general model for estimation can be observed below. In the main equation Y is a dependent variable, T, Dt, and their multiplication are independent variables with β, γ, and δ coefficients, respectively, and α is a constant, ε is an error term, where T stands for treatment dummy variable with control group being equal to 0 and treatment group being 1, and Dt is a time dummy variable with 1 standing for observations taken after the treatment and 0 for observations before the treatment. The multiplication of both treatment and time variables is the interaction variable, whose coefficient δ determines the difference in differences.

$$Y = \alpha + \beta T + \gamma \, \mathrm{Dt} + \delta(\mathrm{T} \times \mathrm{Dt}) + \varepsilon$$

$$E\ (Y \mid T = 0,\ Dt = 0) = \alpha \qquad E\ (Y \mid T = 0,\ Dt = 1) = \alpha + \gamma$$

$$E\ (Y \mid T = 1,\ Dt = 0) = \alpha + \beta \qquad E\ (Y \mid T = 1,\ Dt = 1) = \alpha + \beta + \gamma + \delta$$

	Treatment group (T=1)	Control group (T=0)	Difference
Before the treatment (Dt=0)	$\alpha+\beta$	α	β
After the treatment (Dt=1)	$\alpha+\beta+\gamma+\delta$	$\alpha+\gamma$	$\beta+\delta$
Change	$\gamma+\delta$	γ	$\boldsymbol{\delta}$

In the difference in differences Stata estimations part, the same example of Card and Krueger (1994) was implemented. The model is given as follows:

$$FTE = \alpha + \beta \, State + \gamma \, \mathrm{After} + \delta(\mathrm{State} \times \mathrm{After})$$

In their research paper, the measure of employment was *FTE* (Full-Time Employment), which was calculated by summing up the number of full-time employees, the number of managers, and ½ times the number of part-time employees:

```
gen fte = empft + nmgrs + 0.5 * empppt
```

In the model, *State* is a treatment dummy variable with New Jersey being equal to 1 and Pennsylvania being equal to 0, and *After* is a time variable for observations after the change in minimum wage being 1 and 0, otherwise. Initially, there were some difficulties in the estimation of diff-in-diff model because the original data obtained from David Card was cross section data, whereas the panel data is required for this estimation. Therefore, the data was transformed appropriately.

The first way of estimating difference in differences model in Stata is generating the interaction variable and regressing our model with robust standard errors:

```
gen did = state * after
```

```
. reg fte state after did, vce(robust)

Linear regression                               Number of obs     =        794
                                                F(3, 790)         =       1.40
                                                Prob > F          =     0.2404
                                                R-squared         =     0.0074
                                                Root MSE          =     9.4056
```

fte	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
state	-2.891761	1.438696	-2.01	0.045	-5.71588	-.067642
after	-2.165584	1.641212	-1.32	0.187	-5.387236	1.056067
did	2.753606	1.795451	1.53	0.126	-.7708128	6.278024
_cons	23.33117	1.345741	17.34	0.000	20.68952	25.97282

The reported table indicates both the coefficients and p-values of the right-hand side variables in the model, although the observed p-value of δ (*did*) is 0.126 which may not be good enough. The estimates can also be compared with the original estimates of Card and Krueger (1994):

TABLE 3—AVERAGE EMPLOYMENT PER STORE BEFORE AND AFTER THE RISE IN NEW JERSEY MINIMUM WAGE

Variable	Stores by state		
	PA (i)	NJ (ii)	Difference, NJ – PA (iii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	–2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	–0.14 (1.07)
3. Change in mean FTE employment	–2.16 (1.25)	0.59 (0.54)	2.76 (1.36)

The estimates of both tables are more or less same with t statistics being slightly different in general. Furthermore, the graphical representation of difference in differences of the average employment in fast food sectors of New Jersey and Pennsylvania states, which was retrieved from re-estimation of the same paper of Card and Krueger as a reply for numerous critiques (2000), can be observed:

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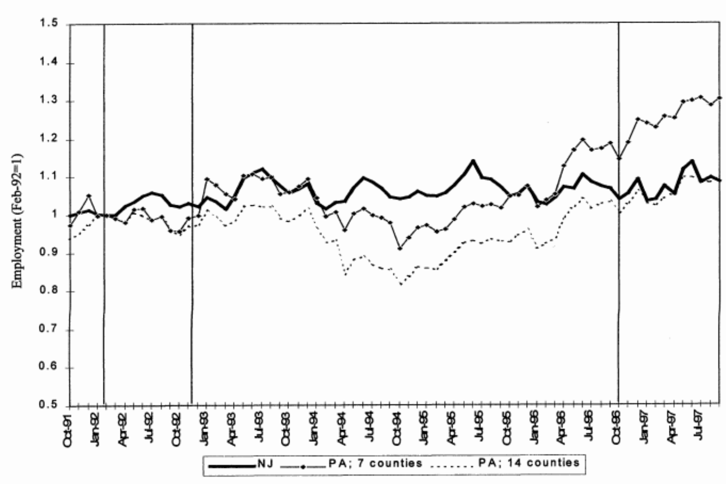

FIGURE 2. EMPLOYMENT IN NEW JERSEY AND PENNSYLVANIA FAST-FOOD RESTAURANTS, OCTOBER 1991 TO SEPTEMBER 1997

Note: Vertical lines indicate dates of original Card-Krueger survey and the October 1996 federal minimum-wage increase.
Source: Authors' calculations based on BLS ES-202 data.

The second way of estimating difference in differences model in Stata is a bit shorter without generating the interaction variable:

```
. reg fte state##after, vce(robust)

Linear regression                               Number of obs     =        794
                                                F(3, 790)         =       1.40
                                                Prob > F          =     0.2404
                                                R-squared         =     0.0074
                                                Root MSE          =     9.4056

------------------------------------------------------------------------------
             |               Robust
         fte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     1.state |  -2.891761   1.438696    -2.01   0.045     -5.71588   -.067642
     1.after |  -2.165584   1.641212    -1.32   0.187    -5.387236   1.056067
             |
 state#after |
        1 1  |   2.753606   1.795451     1.53   0.126    -.7708128   6.278024
             |
       _cons |   23.33117   1.345741    17.34   0.000     20.68952   25.97282
------------------------------------------------------------------------------
```

As seen in the table, all the estimates are same with those in the first method; however, the places and titles slightly differ.

The third way comprises the installation of diff-in-diff package to Stata, which can be done easily by typing several commands:

```
ssc install diff
```

After a while, when the package is installed, the difference in differences model can be estimated, with treatment variable being in the first parentheses and time variable being in the second:

```
diff fte, t(state) p(after)
```

The output for the third way can be observed below. Compared to the previous estimations, the table here is more convenient. It includes the sample sizes and mean employments for all states, making it easier to grasp. However, the estimates do not use the robust standard errors.

To sum up, difference in differences methodology is very crucial and interesting in theory and easy in its application.

DIFFERENCE-IN-DIFFERENCES ESTIMATION RESULTS

Number of observations in the DIFF-IN-DIFF: 794

	Before	After	
Control:	77	77	154
Treated:	321	319	640
	398	396	

Outcome var.	fte	S. Err.	|t|	P>|t|
Before				
Control	23.331			
Treated	20.439			
Diff (T-C)	-2.892	1.194	-2.42	0.016**
After				
Control	21.166			
Treated	21.027			
Diff (T-C)	-0.138	1.194	0.12	0.908
Diff-in-Diff	2.754	1.688	1.63	0.103

R-square: 0.01

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1

References

Card, D., & Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania. *The American Economic Review*, *84*(4). Retrieved December 19, 2018, from http://davidcard.berkeley.edu/papers/njmin-aer.pdf

Card, D., & Krueger, A. (2000). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply. *The American Economic Review*, *90*(5), 1397-1420. Retrieved from http://www.jstor.org/stable/2677856

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Torres - Reyna, O. (n.d.). *Differences-in-differences (using Stata)* [Scholarly project]. In *Princeton University*. Retrieved December 20, 2018, from http://www.princeton.edu/~otorres/DID101.pdf