

Today:

Extend linear regression to make the most of natural experiment type data;

▶ Work through a case study applying difference in differences.

So far, we've used linear regression to:

1. Model a linear relationship between dependent variable y and independent variable x:

$$y = \beta_0 + \beta_1 x + \varepsilon;$$

2. Model a linear relationship between dependent variable y and many independent variables x_1, x_2, x_3, \ldots :

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \varepsilon;$$

3. Model a NON-linear relationship between dependent variable y and many independent variables x:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \ldots + \varepsilon;$$

4. Model relationships between independent variables:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon;$$



Motivation...

Does increasing the minimum wage decrease employment?

Motivation...

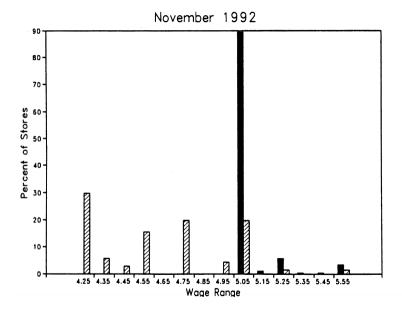
- ▶ In early 1990 NJ raised the minimum wage from \$4.25 to \$5.05 effective 1 April 1992 – highest minimum wage in the country;
- Notably, nearby eastern PA maintained a lower minimum wage;
- A natural within-subjects experiment;
 - NJ employers before/after;
 - PA employers before/after;
- Card and Krueger surveyed 473 fast food restaurants before and after law;
 - Low wage workers;
 - High response survey response rate.



TABLE 1—SAMPLE DESIGN AND RESPONSE RATES

		Stores in:	
	All	NJ	PA
Wave 1, February 15 - March 4, 1992:			
Number of stores in sample frame: ^a	473	364	109
Number of refusals:	63	33	30
Number interviewed:	410	331	79
Response rate (percentage):	86.7	90.9	72.5
Wave 2, November 5 - December 31, 1992:			
Number of stores in sample frame:	410	331	79
Number closed:	6	5	1
Number under rennovation:	2	2	0
Number temporarily closed: ^b	2	2	0
Number of refusals:	1	1	0
Number interviewed: ^c	399	321	78

February 1992 30 -25 Percent of Stores 20-15-10-4.25 4.35 4.45 4.55 4.65 4.75 4.85 4.95 5.05 5.15 5.25 5.35 5.45 5.55 Wage Range



Recall...

▶ If the researcher controls assignment of independent variables to observations (e.g. selection of treatment and control groups) then the data is experimental;

- A natural experiment is a situation in which:
 - ► The researcher does NOT control assignment of independent variables to observations...
 - ...but whatever does ends up creating a psuedo-randomly assigned treatment and control group anyway.

➤ So, can we extend linear regression to deal with observational data that has the characteristics of an experiment?

- ▶ Say we have data in which we measure the dependent variable for four groups:
 - 1. ...a 'treatment' group before treatment
 - 2. ...a 'treatment' group after treatment
 - 3. ...a 'control' group before no treatment
 - 4. ...a 'control' group after no treatment

- ▶ Say we have data in which we measure the dependent variable for four groups:
 - 1. ...a 'treatment' group before treatment (fast food restaurants NJ early 1992);
 - 2. ...a 'treatment' group after treatment (fast food restaurants NJ late 1992);
 - 3. ...a 'control' group before no treatment (fast food restaurants PA early 1992);
 - 4. ...a 'control' group after no treatment (fast food restaurants PA late 1992);

- ▶ Say we have data in which we measure the dependent variable for four groups:
 - 1. ...a 'treatment' group before treatment (fast food restaurants NJ early 1992);
 - 2. ...a 'treatment' group after treatment (fast food restaurants NJ late 1992);
 - 3. ...a 'control' group before no treatment (fast food restaurants PA early 1992);
 - 4. ...a 'control' group after no treatment (fast food restaurants PA late 1992);
- ► This data could look something like:

Unit ID	T (time)	G (state)	$y \ (\# \ ext{of employees})$
fast food restaurant 1	0 (early 1992)	1 (NJ)	10
fast food restaurant 1	1 (late 1992)	1 (NJ)	11
fast food restaurant 2	0 (early 1992)	0 (PA)	15
fast food restaurant 2	1 (late 1992)	0 (PA)	12
:	:	:	:
fast food restaurant 473	0 (early 1992)	1 (NJ)	25
fast food restaurant 473	1 (late 1992)	1 (NJ)	32

Let's run a simple linear regression to analyze this data:

$$y = \beta_0 + \beta_1 T + \beta_2 G + \beta_{12} (TG) + \varepsilon$$

- As usual, in this linear regression equation:
 - ▶ y is the dependent variable it comes from data;
 - T is an indicator that is a 1 for after treatment and 0 for before treatment;
 - ightharpoonup G is an indicator that is 1 for treatment group and 0 for control group;
 - ightharpoonup the eta's are the effects linear regression will learn these from data;
 - \triangleright ε is noise we don't get to observe this;

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- As usual, in this linear regression equation:
 - ▶ *y* is the dependent variable it comes from data;
 - T is an indicator that is a 1 for late 1992 and 0 for early 1992;
 - G is an indicator that is 1 for NJ and 0 for PA;
 - \blacktriangleright the β 's are the effects linear regression will learn these from data;
 - \triangleright ε is noise we don't get to observe this;

Let's run a simple linear regression to analyze this data:

$$y = \beta_0 + \beta_1 T + \beta_2 G + \beta_{12} (TG) + \varepsilon$$

• Check out β_{12} – it can be shown (though we won't) that:

$$\beta_{12} = (\overline{y}_{11} - \overline{y}_{01}) - (\overline{y}_{10} - \overline{y}_{00})$$

 $ightharpoonup \overline{y}_{TG} = ext{average dependent variable for group } G ext{ at time } T;$

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- $ightharpoonup \overline{y}_{TG} = ext{average dependent variable for group } G ext{ at time } T;$
- $ightharpoonup \overline{y}_{11} =$ average dependent variable for the treatment group after treatment;
- $ightharpoonup \overline{y}_{01} =$ average dependent variable for the treatment group before treatment;
- ightharpoons $\overline{y}_{10}=$ average dependent variable for the control group after treatment;
- ightharpoons $\overline{y}_{00}=$ average dependent variable for the control group before treatment;

Let's run a simple linear regression to analyze this data:

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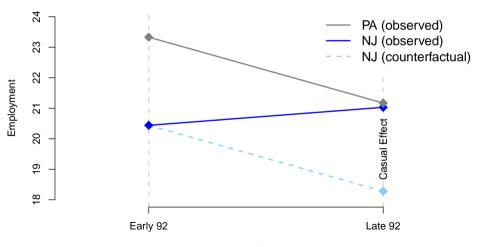
- \overline{y}_{TG} = average dependent variable for group G at time T;
- $ightharpoonup \overline{y}_{11} = \text{average employment for the NJ restaurants, late 92};$
- $ightharpoonup \overline{y}_{01} = \text{average employment for the NJ restaurants, early 92};$
- \overline{y}_{10} = average employment for the eastern PA restaurants, late 92;
- \overline{y}_{00} = average employment for the eastern PA restaurants, early 92;

$$eta_{12} = (\widetilde{\overline{y}_{11}}^{ ext{NJ, late }92} - \widetilde{\overline{y}_{01}}^{ ext{NJ, early }92}) - (\widetilde{\overline{y}_{10}}^{ ext{PA, late }92} - \widetilde{\overline{y}_{00}}^{ ext{PA, early }92})$$

$$eta_{12} = \underbrace{(\overbrace{\overline{y}_{11}}^{ ext{NJ, late }92} - \overbrace{\overline{y}_{01}}^{ ext{NJ, early }92}}_{ ext{Difference w/i Treatment}} - \underbrace{(\overbrace{\overline{y}_{10}}^{ ext{PA, late }92} - \overbrace{\overline{y}_{00}}^{ ext{PA, early }92})}_{ ext{Difference w/i Control}}$$

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Parallel Trend Assumption



So, does increasing minimum wage decrease employment?

	NJ	PA	Difference
Early 92	20.44	23.33	-2.89
Late 92	21.03	21.17	-0.14
Change	0.59	-2.16	2.75

$$\beta_{12} = (\overline{y}_{11} - \overline{y}_{01}) - (\overline{y}_{10} - \overline{y}_{00})$$

So, does increasing minimum wage decrease employment? Nope!

	NJ	PA	Difference
Early 92	20.44	23.33	-2.89
Late 92	21.03	21.17	-0.14
Change	0.59	-2.16	2.75

$$\beta_{12} = (\overline{y}_{11} - \overline{y}_{01}) - (\overline{y}_{10} - \overline{y}_{00})$$

$$\beta_{12} = (21.03 - 20.44) - (21.17 - 23.33) = 2.75.$$

Why should we care?

Experiments are the gold standard in establishing causality and we can use linear regression to model the data they generate.