Causal Inference as Making Good Comparisons
Assessing the Impact of Minimum Wages

ECON 490

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Slides Overview

In these slides, we'll talk about:

- Causal inference in terms of making good comparisons
- Economic studies of the effects of the minimum wage

Making Good Comparisons

Goal of causal inference is to identify the causal effect of some treatment

- Let's say X is binary – we want to know, if you get X, what happens?
- Assessing the effect of $X = 1$ requires a ***comparison group*** with $\mathrm{X} = 0$

Why do we need a comparison group?

- We want to estimate the change in some outcome Y given X
- If everyone had $X = 1$ then how can we isolate the effect of X?

Given a comparison group, calculate effect of X as difference in means

- Compare Y for those with $X = 0$ and $X = 1$

Finding the Right Comparison Group

Let's say we've found a possible comparison group of people with $X = 0$

- **<u>Q:</u>** What does it mean for this group to be a "good" comparison group?
- **<u>A:</u>** The more similar they are to people with $X = 1$, the better!

Question: If similarity is good, why not just use myself as the comparison group?

- Suppose we track your Y before and after switching $X = 0$ to $X = 1$
- What if X isn't the only thing changing about you over time?

We can't know what your Y would be if we never switched X

- In econometrics terms, we can't observe ***counterfactual*** you

Selection

When you run an experiment or randomized control trial…

- Treatment X is randomly assigned to people
- Meaning you're not worried about ***why*** some people got X and others didn't

With randomization (and enough trial participants), we can identify effect of treatment as difference in average Y for $X = 1$ and $X = 0$

When we ***can't*** do an experiments, what happens?

- We need to worry about why each person got $X = 1$ instead of $X = 0$
- In other words, worried about ***selection***

Making Selection Intuitive

When we say selection, we mean, "Why you have the value of X that you do?"

- In OVB terms, we're often concerned that this "why" is also correlated with Y

Multivitamin example – do multivitamins make you healthier?

- ***Selection:*** Healthier people might be more likely to take multivitamins (MV)
- ***OVB:*** We conflate specific health effect of MV with general health differences

College major example – how does a specific college affect your earnings?

- ***Selection:*** Your choice of major says a lot about your priorities
- ***OVB:*** We conflate specific major effect with general differences in the priority that people place on maximizing career earnings

Comparisons with Fixed Effects

Let’s think about our test score ~ hours spent studying example

- Without a student FE, systematic differences across students were a problem
- We were making bad comparisons!

By including a fixed effect for student, we allowed for ***relative*** comparisons

- Relative to a student’s own baseline study habits, did they study more?
- If so, how did they score relative to their baseline performance?

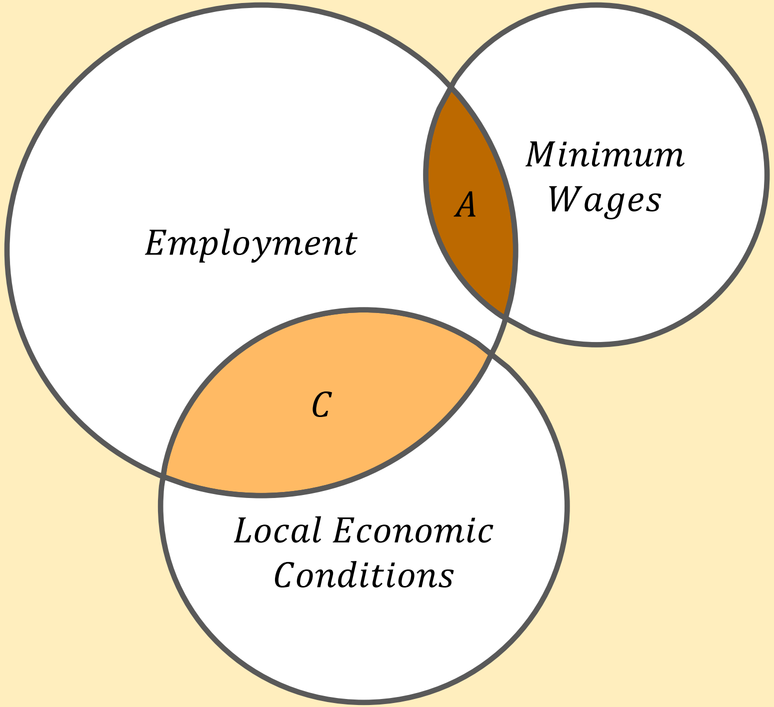
In general, adding fixed effects changes the kinds of comparison we make

Randomization as a Benchmark

Use Venn Diagram model as a starting point to think about identifying the causal effect of MW

If states let us randomly assign MW, this would be easy…

Not likely to happen, however!



The Real World

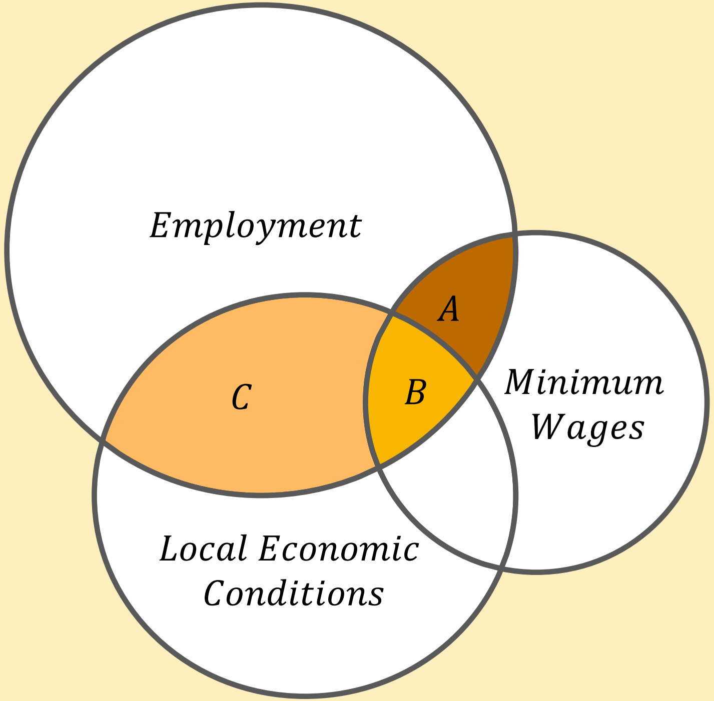
In practice, this is the Venn Diagram we face

- States can set their own MWs
- They may do so in ways that are correlated with state economic conditions

Causal inference as a ***selection*** or ***attribution*** problem

- What is the effect of MW vs. local conditions?

Goal is to isolate unique variation in MW



Setting the Stage

ECON 101 supply and demand model makes clear predictions about MW

- Assuming we have a ***binding*** MW in a ***perfectly competitive*** market…
- We should expect a surplus of labor supplied = unemployment

Given this clear prediction, it might be surprising to learn there's been decades of minimum wage research!

Why is this? Assumptions above matter, research methods improve, …

Historical Studies of the Minimum Wage

Through the 1970's and 1980's, papers used a "cross-sectional" approach

- Collect data from CPS survey on employment, demographic variables, etc.
- Include some continuous measure of business cycle / economic output

Aggregate your data to the national level and estimate something like:

$$Employment_t = \alpha_0 + \alpha_1 MW_t + \alpha_2 X_t + \alpha_3 Z_t + u_t$$

These kinds of studies tended to find negative employment effects of MW

- Negative employment elasticities of -0.1 to -0.3 for 16-to-19-year-olds

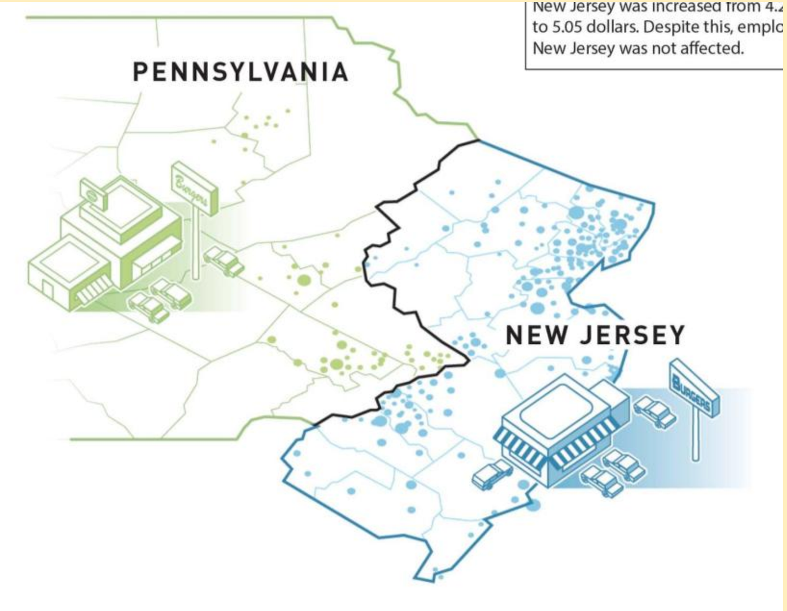
A Turning Point

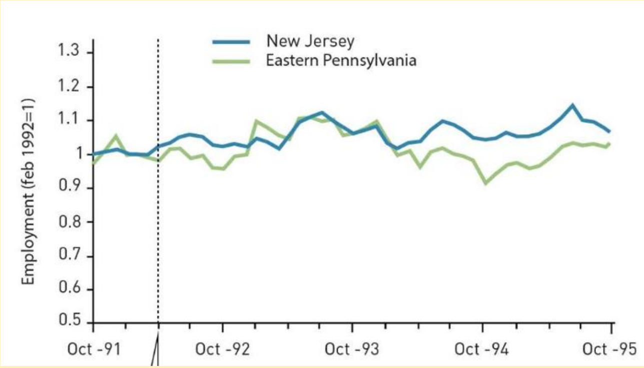
Card and Krueger (1994) is one of the most famous applied economics papers

In 1992, NJ increased MW from $4.25 to $5.05

- Authors collected data from NJ and eastern Pennsylvania where there was ***no*** MW change
- Surveyed restaurants on wages & employment

Found ***no*** evidence of employment reductions





Minimum Wage Studies in the 1990's and 2000's

Card and Krueger "zoomed in" to consider just NJ's MW change

- But over the last 3 decades, there's been lots of changes to MW across states
- What if we want to estimate the effect of all those changes?

Lots of studies ran variations of the following:

$$Employment_{st} = \alpha_0 + \alpha_1 MW_{st} + \gamma_s + \tau_t + \epsilon_{st}$$

In R, this is: `lm(emp ~ MW + as.factor(state) + as.factor(year), data)`

Two-Way Fixed Effects Estimates of Minimum Wages

TWFE regression on the last slide has the advantage of using all MW changes

- It’s kind of a “cookbook” approach to causal inference + diff-in-diff
- If you assume TWFE absorb all possible OVBs, you’ve got a causal effect!

Studies that used this sort of approach often found negative effects of MWs

- Reductions in employment for younger, less-skilled workers
- Tend to be a bit larger than prior estimates; elasticities b/w -0.2 to -0.5

Is this all we need to do? What about finding credible comparison groups?

Modern Studies of Minimum Wages

Lots of methodological advances in the last 5 years

- Affecting how we ***estimate*** DiD models (no more `lm()` with TWFE!)
- Also increasing attention paid to identifying credible comparison groups

Dube et al. (2010) – what makes a good comparison group?

- TWFE papers say, “Let’s use all states”
- Dube and co-authors ask, “Does that give us the comparisons we want?”

Their approach is a generalization of C & K – look at cross-border differences

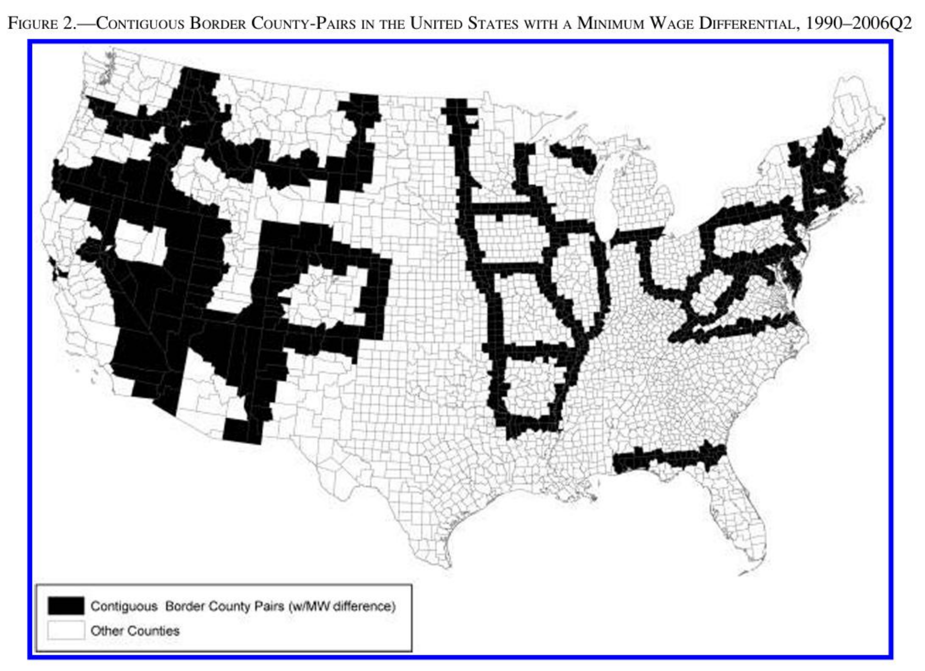
Dube et al. (2010)

Find pairs of treatment and control counties across state borders

Restrict sample to just these pairs

- Do border counties make good comparison groups?
- More likely to share local economic shocks, conditions, etc.

They find no effect of MW on emp.



Descriptive vs. Causal Questions

DiD and related models appear everywhere in modern economics research

- We discuss these models to make modern research more approachable
- Remember that these research designs are intended for ***causal*** analysis

What if you're doing a descriptive analysis? TWFE with `lm()` can help a lot!

- Despite the methodological shortcomings, it's still an easy way to absorb lots of potential sources of OVB
- Allows you to compare the impact of a variable changing within a particular area, over time (i.e. controlling for avg. area and avg. shared time differences)

Summarizing the Minimum Wage Literature

Okay, we've talked a lot about causal inference, but what do MWs actually do?!

- For changes within range we've seen historically ($1-2), probably not a lot
- Very little evidence of "macro-scale" effects

However, some limited evidence for disemployment effects for larger changes for demographic groups most likely to be impacted

Note that larger changes could have different effects!

- Internal validity = does this study "work" on its own terms
- External validity = what does this tell us about the future, other settings, etc.?