14.03/003 Micro Theory & Public Policy, Fall 2025

Lecture Slides 2 and 3. The Minimum Wage Debate: Theory Meets Causal Inference

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Reminders

- Make a name card if you don't already have one
- Register your Plickers card with Emma Zhu on Slack if not already registered
- Pset 1 due Thursday, 9/18 at 11:59 EST on Gradescope, *late submissions not accepted*

Outline

1. ✓ Textbook model of competitive labor market
   - □ Impact of minimum wage on employment in the textbook model
   - □ Assumptions behind this model
2. Relax a key assumption: price-taking by firms
   - □ Impact of min. wage on employment when employers have market power
   - □ Testing the textbook model and alternatives
3. Natural experiments in economics
4. The Fundamental Problem of Causal Inference
5. Estimating causal effects using "Differences-in-Differences" (DD)
6. The Card and Krueger minimum wage study
7. A word on the methodology of economics

Monopsonistic employer

Definition (Monopoly)

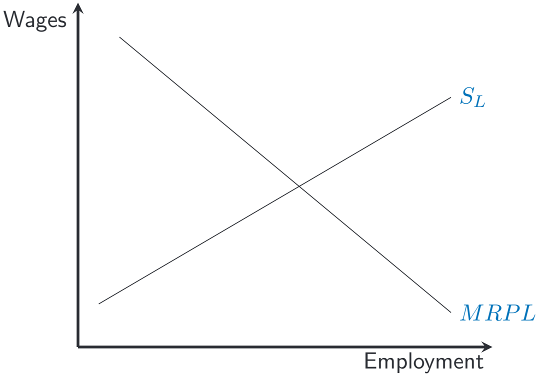
One seller, many buyers

Definition (Monopsony)

One buyer, many sellers

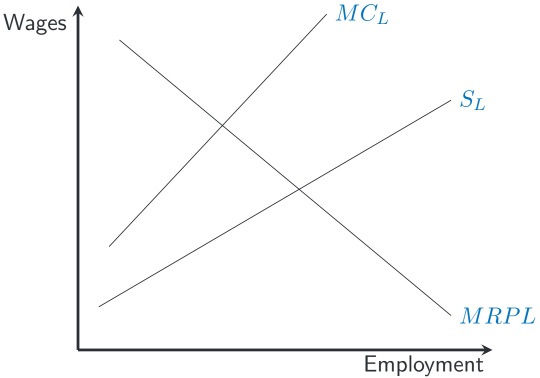
- More generally, a market where a buying agent is not a *price-taker*
- If a firm has labor market power—it is not a price-taker—its own demand for labor affects the market wage
- Examples?

Monopsonistic employer



1. S_L is upward sloping for a monopsonist.
2. If all workers receive the same wage, the marginal cost of a worker includes a raise given to all inframarginal workers.
3. Thus, MC_L is *even more* upward sloping than S_L.

Monopsonistic employer



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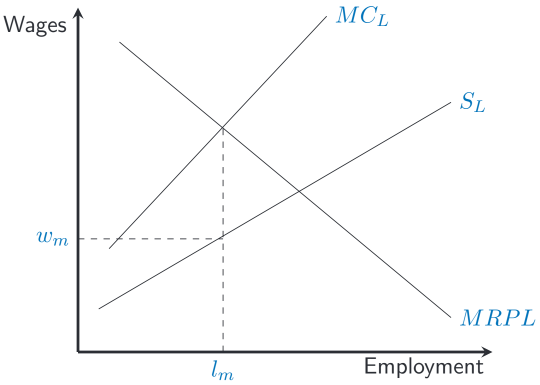

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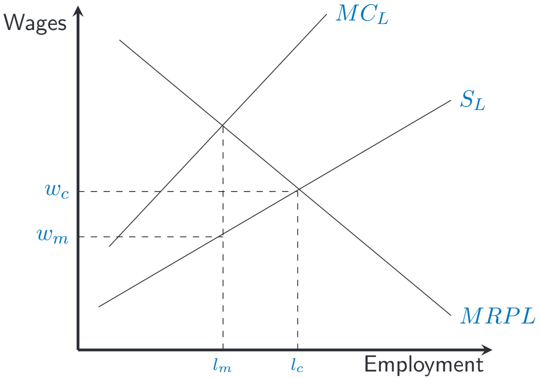

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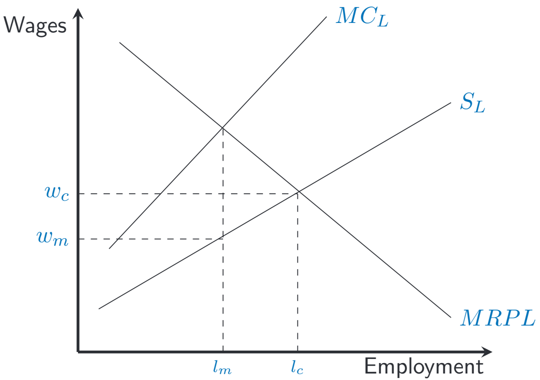
Raising the minimum wage on a monopsonistic employer



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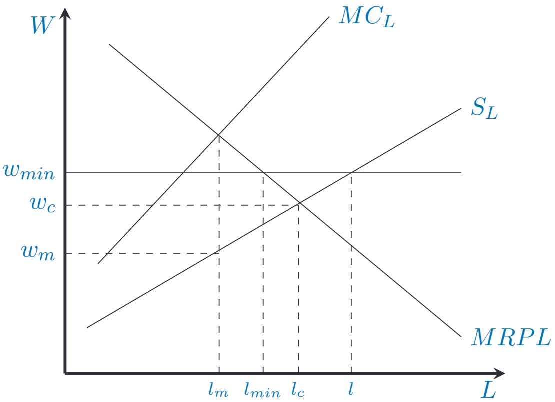
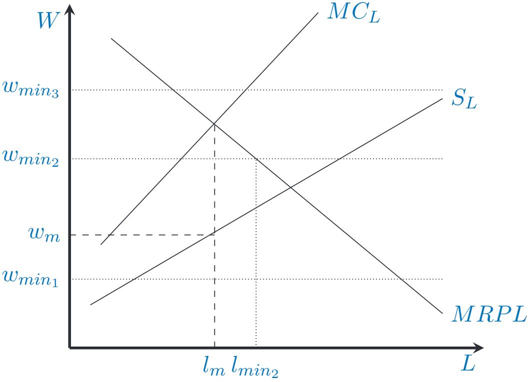
Raising the minimum wage on a monopsonistic employer



- Why did we get $w_{\text{min}} > w_m, l_{\text{min}} > l_m$?
  - The firm is now a *price-taker* for labor at w_{min}
  - Firm chooses l_{min} so that $w_{\text{min}} = MRPL$

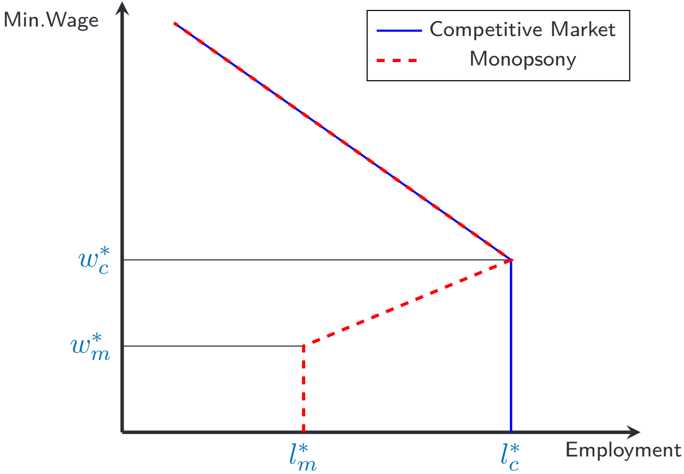
Raising the minimum wage on a monopsonistic employer

- Does raising minimum wage to monopsonists *always* increase employment?



Effect of a minimum wage

Monopsony vs. competitive market



Relationship between labor supply elasticity and marginal cost of labor

- Why is $w^* = MRPL$?
- Firm's profit maximization problem:

$$\max \ \pi = p \cdot f\left(l\right) - w(l) \cdot l,$$

  - Assume that $f'\left(\cdot\right) > 0$ and $f''\left(\cdot\right) < 0$, and p is exogenous.

- FOC:

$$\frac{\partial \pi}{\partial l} = p \cdot \frac{\partial f\left(l\right)}{\partial l} - w(l) - \frac{\partial w(l)}{\partial l} \cdot l = 0$$

Rearranging:

$$\overbrace{pf'(l)}^{MRPL} = \overbrace{w(l)}^{\text{wage of new hire}} + \overbrace{w'(l)l}^{\Delta\text{total labor costs}}$$

Relationship between labor supply elasticity and marginal cost of labor

- Third term is critical for monopsonist

$$\overbrace{pf'(l)}^{MRPL} = \overbrace{w(l)}^{\text{wage of new hire}} + \overbrace{w'(l)l}^{\Delta\text{total labor costs}}$$

- *Competitive* model

$$w'(l) = 0 \iff \text{Price taking firm}$$

- *Monopsonistic* model

$$w'(l) > 0 \iff \text{Monopsonistic firm}$$

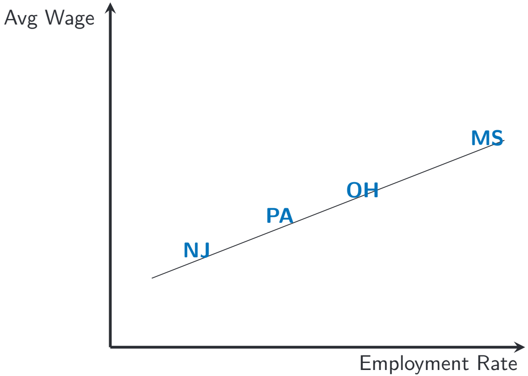
- Re-arranging in terms of the elasticity of labor supply (σ_s)

$$MRPL = w\left(1 + \frac{\partial w}{\partial l}\frac{l}{w}\right) = w\left(1 + \frac{1}{\sigma_s}\right)$$

- If the firm is not a price taker ($\sigma_s < \infty$) in the labor market, then the wage it pays is *strictly less* than MRPL.

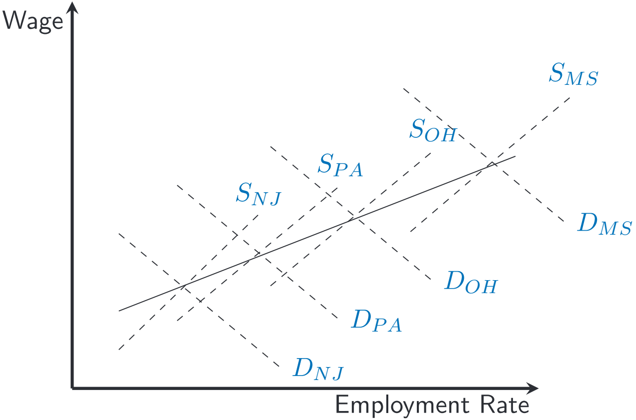
Testing for monopsony in the labor market

- Let's suppose you find the following pattern:



- Would this convince you that higher wage levels *caused* higher employment?

Testing for monopsony in the labor market



Testing for monopsony in the labor market

- A profound empirical problem
  - We do not ever see supply and demand curves
  - We observe *only* equilibrium wage and quantity employed
  - Cannot directly see if individual firms face upward sloping labor supply
- How do we overcome this problem?
  - **We need an experiment!**
  - **What do we need that experiment to change exogenously?**
  - *We need an experiment in which minimum wages are raised exogenously at a subset of firms*

David Card and Alan B. Krueger, 1994 (American Economic Review)

Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania

By DAVID CARD AND ALAN B. KRUEGER*

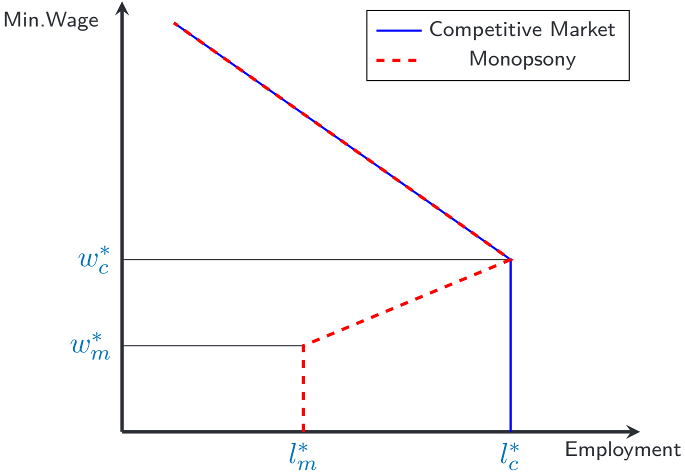
On April 1, 1992, New Jersey's minimum wage rose from \$4.25 to \$5.05 per hour. To evaluate the impact of the law we surveyed 410 fast-food restaurants in New Jersey and eastern Pennsylvania before and after the rise. Comparisons of employment growth at stores in New Jersey and Pennsylvania (where the minimum wage was constant) provide simple estimates of the effect of the higher minimum wage. We also compare employment changes at stores in New Jersey that were initially paying high wages (above \$5) to the changes at lower-wage stores. We find no indication that the rise in the minimum wage reduced employment. (*JEL* J30, J23)

Testing for monopsony in the labor market

- **How do we use this 'natural experiment' to test the competitive model against alternatives?**
- **Use key empirical implications**
  - In the competitive model, an increase in the minimum wage always reduces employment: $w_{min} \uparrow \rightarrow l \downarrow$
  - In the monopsonistic model, an increase in the minimum wage *may* raise employment: $w_{min} \uparrow \rightarrow l \uparrow$
  - Downward sloping $\rightarrow$ competitive market
  - Upward sloping $\rightarrow$ monopsony

Effect of a minimum wage

Monopsony vs. competitive market



What is a “Causal Effect” —
And how do we measure it?

Correlations vs. causal effects

- Correlations are all around us and are often mistaken for causal relationships
  - Correlations are useful for making predictions about things that are associated
  - Example: people with high income tend to be healthier than average — an association
  - It does not follow that if you raised someone's income, they'd get healthier, or if their health improved, their income would rise
  - These things could happen, but the correlations are not informative about the causal effects
- Science advances by revealing cause and effect—the effect of action X on outcome Y
  - Causal questions are harder to answer than correlational questions
  - This is because causal effects can *never* be measured directly
  - Causal questions intrinsically concern a ***counterfactual* state**

What is a causal effect?

- Imagine two potential outcomes $Y_i \in \{Y_{0i}, Y_{1i}\}$ for every unit i
- i could be a water molecule, a person, a country, etc.
- Which outcome of Y_i is **realized** depends upon on the variable X_i
  - if $X_i = 0$, then $Y_i = Y_{i0}$
  - if $X_i = 1$, then $Y_i = Y_{i1}$
- We say that the **causal effect** of X_i on Y_i is

$$T_i = Y_{1i} - Y_{0i},$$

where T_i stands for the Treatment Effect of X_i on Y_i

The fundamental problem of causal inference (FPCI)

- The causal effect of X_i on Y_i is

$$T_i = Y_{1i} - Y_{0i},$$

  where T stands for Treatment Effect

- Problem
  - We observe only

$$Y_i = Y_{1i}X_i + Y_{0i}\left(1 - X_i\right)$$

  - We never observe both $\{Y_{1i}, Y_{0i}\}$ and hence cannot calculate $Y_{1i} - Y_{0i}$

- We therefore can never measure the causal effect of X_i on Y_i

Definition (Fundamental Problem of Causal Inference)

It's not possible to observe the value Y_{1i} and Y_{0i} for the same unit i,
$\longrightarrow$ We *cannot* measure the causal effect of X on Y for unit i

Mission Impossible I — Assume 'Stability' + 'Reversibility'

Work-around I: Postulate stability and reversibility

- **Claim:** If the causal effect of X_i on Y_i is
  1. **Temporally stable:** the same at every point in time, *and*
  2. **Reversible (memoryless):** Undoing the cause reverses the effect

     $Y_{1i,t} = Y_{1i} \, \forall \, t$, and $Y_{oi,t} = Y_{oi} \, \forall \, t$

  - We can therefore observe $Y_{1i} - Y_{0i}$ by repeatedly changing X_i from 0 to 1
  - The causal effect of X_i on Y_i is $\rightarrow T_i = (Y_i|X_i = 1) - (Y_i|X_i = 0)$
- Issues?
  - Temporal stability and causal transience cannot be tested
  - These assumptions may not always be plausible
- Examples/counter-examples:
  - Water from ice to steam and back
  - Treatment for high cholesterol for patient i

Mission Impossible II — Assume 'Unit Homogeneity'

Work-around II: Postulate unit homogeneity (interchangeability)

- **If the following is true**
  - Y_{1i} and Y_{0i} are identical for all i
  - Implies that $Y_{1i} = Y_1 \,\forall\, i$ and $Y_{0i} = Y_0 \,\forall\, i$
- Then
  - The causal effect of X_i on Y_i is simply the difference:

$$T_i = T = Y_{1i} - Y_{0j} \;\forall i \neq j$$

Work-around II: Postulate unit homogeneity (interchangeability)

- **If the following is true**
  - Y_{1i} and Y_{0i} are identical for all i
  - Implies that $Y_{1i} = Y_1 \, \forall \, i$ and $Y_{0i} = Y_0 \, \forall \, i$

- Then
  - The causal effect of X_i on Y_i is simply the difference:

$$T_i = T = Y_{1i} - Y_{0j} \, \forall i \neq j$$

- **Examples/counterexamples**
  - Water molecules
  - Treatment for high cholesterol for patient i

- This is plausible *only* under certain laboratory conditions

Mission Impossible III — Adjust the target *and* run experiments

Work-around III: Adjust the target, and run experiments

We will never learn a causal effect for a specific person

- For human subjects, neither (1) temporal stability and causal transience nor (2) unit homogeneity are ever plausible

Must acknowledge that we cannot estimate

$$T_i = Y_{1i} - Y_{0i} \text{ for a person } i$$

Instead, we estimate population effects

Estimating Average Treatment Effect on the Treated (ATT)

- Average Treatment Effect on the Treated

$$T^* = E[Y_1 - Y_0 | X = 1],$$

- One idea
  - Compare $E[Y|X=1]$ and $E[Y|X=0]$ to form

$$\tilde{T} = E[Y|X=1] - E[Y|X=0]$$

- Is this a good idea?
  - Consider cholestorol treatment drug
  - We want to identify a set of treatment/control people for whom the counterfactual outcomes are comparable

Treatment-control balance
(‘exchangeability’)

Estimating ATT

- **Want to identify a set of treatment/control people for whom the counterfactual outcomes are comparable**
- **Treatment-control balance (exchangeability):**

$$E\left[Y_1|X=1\right]=E\left[Y_1|X=0\right]$$
$$E\left[Y_0|X=1\right]=E\left[Y_0|X=0\right]$$

  - Where $E[\cdot]$ is the *expectation* operator
  - $E[\cdot]$ denotes the mean (i.e., expected value) of a random variable (RV).
  - And $E[\cdot|\textsc{Condition}]$ denotes the expected value of the RV in cases where the $\textsc{Condition}$ is true.
- If treatment and control groups are balanced, we can say that assignment to treatment is *ignorable* and the groups are *exchangeable*
  - You could swap the treatment and control groups (before the experiment) and get the same treatment effect estimate (on average)

Estimating ATT

- Treatment-control balance (exchangeability):

$$E[Y_1|X=1] = E[Y_1|X=0]$$
$$E[Y_0|X=1] = E[Y_0|X=0].$$

- If these conditions are satisfied, then we can use the difference for the treatment and control group:

$$\begin{aligned} E[Y_1|X=1] - E[Y_0|X=0] &= E[Y_1|X=1] - E[Y_0|X=1] \\ &= T^* \end{aligned}$$

- Notice that this substitution **requires** the treatment-control balance condition:

$$E[Y_0|X=0] = E[Y_0|X=1].$$

What if the treatment-control balance condition is not satisfied?

- What if compare cholesterol drug-takers to non-takers without a randomized experiment

$$E\left[Y_1|X=1\right] \lesseqgtr E\left[Y_1|X=0\right]?$$
$$E\left[Y_0|X=1\right] \lesseqgtr E\left[Y_0|X=0\right]?$$

What if the treatment-control balance condition is not satisfied?

- In the cholesterol example, what would we expect for treatment control balance or imbalance?

$$E\left[Y_1|X=1\right] \lesseqgtr E\left[Y_1|X=0\right]?$$
$$E\left[Y_0|X=1\right] \lesseqgtr E\left[Y_0|X=0\right]?$$

- In the cholesterol example, the treatment-control balance condition is likely violated

$$E\left[Y_1|X=1\right] > E\left[Y_1|X=0\right]$$
$$E\left[Y_0|X=1\right] > E\left[Y_0|X=0\right]$$

- Therefore, what would we get if we calculated

$$\tilde{T} = E\left[Y|X=1\right] - E\left[Y|X=0\right]?$$

- Re-write:

$$E\left[Y_1|X=1\right] - E\left[Y_0|X=0\right] = \underbrace{E\left[Y_1|X=1\right] - E\left[Y_0|X=1\right]}_{T^*} + \underbrace{\left\{E\left[Y_0|X=1\right] - E\left[Y_0|X=0\right]\right\}}_{Bias}$$

Implementing the statistical solution using randomization

- Randomly assigned 100 of 200 high cholesterol patients to $D = 1$ and half to $D = 0$
- Randomization guarantees that

$$E[Y_1|D=1] = E[Y_1|D=0]$$
$$E[Y_0|D=1] = E[Y_0|D=0].$$

- Therefore, Treatment-Control Balance should be satisfied (groups are *exchangeable*)
- Now, consider

$$\begin{aligned}\hat{T} &= E[Y_1|D=1] - E[Y_0|D=0] \\ &= E[Y_1|D=1] - E[Y_0|D=1] \\ &+ \underbrace{\{E[Y_0|D=1] - E(Y_0|D=0)\}}_{bias\ =0}.\end{aligned}$$

- Randomization allowed us to estimate the *counterfactual* outcome for the treated group

Average Treatment Effect on the Treated (ATT) vs. Average Treatment Effect (ATE)

Population treatment effects

- Average Treatment Effect for the Treated (ATT):

$$T^* = E\left[Y_1 - Y_0 | X = 1\right],$$

  ATT is the causal effect of the treatment on the people who received the treatment

- Average Treatment Effect (ATE):

$$T^\dagger = E\left[Y_1 - Y_0\right].$$

  ATE is the causal effect one would notionally obtain if *everyone* were treated

Population treatment effects

ATT and ATE are distinct

- The treatment effect of a cholesterol drug given to patients with high cholesterol is *not* likely to equal the treatment effect of a cholesterol drug given to *everyone*
- Often, the ATE is *not of interest* because we would never consider treating people who don't need treatment
- But there are exceptions...

Bottom Line

- Human behavior rarely satisfies temporal stability + causal transience or unit homogeneity

- In contrast, so long as we can randomize, a statistical solution is likely to work (though not always)

- To solve the Fundamental Problem of Causal Inference in economics:
  - If feasible or practical, we use randomized experiments
  - Sometimes, quasi-experiments deliver just the experiment we need
  - In still other cases, we find ingenious workarounds—instrumental variables, regression discontinuity. (We'll talk about these later this term)

The quintessential, classic 'Quasi-experiment'

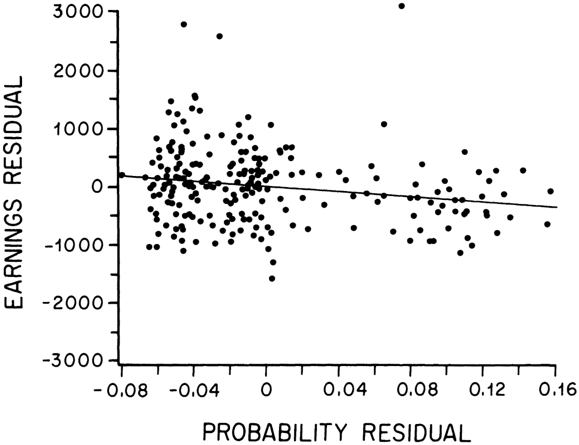
The quintessential quasi-experiment: Vietnam draft lottery

"Selective Service Director Curtis Tarr spins the drum containing the sequence capsules, as the draft lottery got underway in the Commerce Department auditorium," February 2, 1972 (Getty)

Vietnam random number draft lottery sequence in 1972

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1	207	306	364	096	154	274	284	180	302	071	366	038
2	225	028	184	129	261	363	061	326	070	076	190	099
3	246	250	170	262	177	054	103	176	321	144	300	040
4	264	092	283	158	137	187	142	272	032	066	166	001
5	265	233	172	294	041	078	286	063	147	339	211	252
6	242	148	327	297	050	218	185	155	110	006	186	356
7	292	304	149	058	106	288	354	355	042	080	017	141
8	287	208	229	035	216	084	320	157	043	317	260	065
9	338	130	077	289	311	140	022	153	199	254	237	027
10	231	276	360	194	220	226	234	025	046	312	227	362
11	090	351	332	324	107	202	223	034	329	201	244	056
12	228	340	258	165	052	273	169	269	308	257	259	249
13	183	118	173	271	105	047	278	365	094	236	247	204
14	285	064	203	248	267	113	307	309	253	036	316	275
15	325	214	319	222	162	008	088	020	303	075	318	003
16	074	353	347	023	205	068	291	358	243	159	120	128
17	009	198	117	251	270	193	182	295	178	188	298	293
18	051	189	168	139	085	102	131	011	104	134	175	073
19	195	210	053	049	055	044	100	150	255	163	333	019
20	310	086	200	039	119	030	095	115	313	331	125	221
21	206	015	280	342	012	296	067	033	016	282	330	341
22	108	013	345	126	164	059	132	082	145	263	093	156
23	349	116	089	179	197	336	151	143	323	152	181	171
24	337	359	133	021	060	328	004	256	277	212	062	245
25	002	335	219	238	024	213	121	192	224	138	097	135
26	114	136	122	045	026	346	350	348	344	069	209	361
27	072	217	232	124	241	007	235	352	314	098	240	290
28	357	083	215	281	091	057	127	037	005	010	031	174
29	266	305	343	109	081	196	146	279	048	079	230	101
30	268	---	191	029	301	123	112	334	299	087	014	167
31	239	---	161	---	018	---	315	111	---	160	---	322

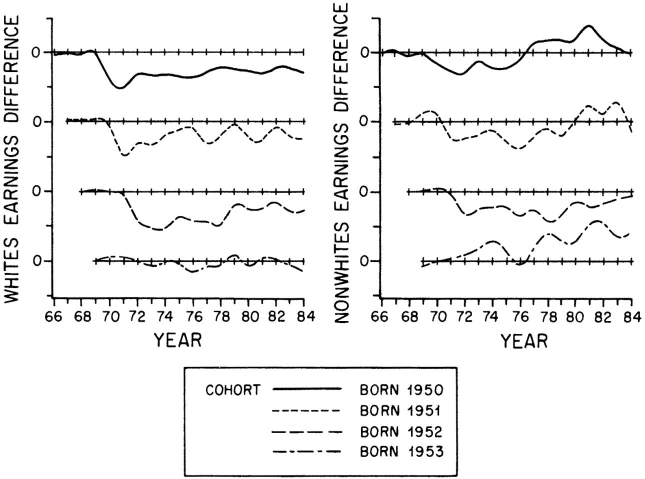
Draft probability and earnings of men from 1951-1993 birth cohorts at ages 25–27



Notes: The figure plots the history of FICA taxable earnings for the four cohorts born 1950–53. For each cohort, separate lines are drawn for draft-eligible and draft-ineligible men. Plotted points show average real (1978) earnings of working men born in 1953, real earnings + \$3000 for men born in 1950, real earnings + \$2000 for men born in 1951, and real earnings + \$1000 for men born in 1952.

FIGURE 1. SOCIAL SECURITY EARNINGS PROFILES BY DRAFT-ELIGIBILITY STATUS

Contrasting earnings of draft eligible/ineligible (due to lottery) men, 1966–1984



Notes: The figure plots the difference in FICA taxable earnings by draft-eligibility status for the four cohorts born 1950–53. Each tick on the vertical axis represents $500 real (1978) dollars.

FIGURE 2. THE DIFFERENCE IN EARNINGS BY DRAFT-ELIGIBILITY STATUS

‘Difference-in-Difference’ estimation

Difference-in-difference estimation

- Often, we don't simply measure the level of Y but it's change as a function of X (the treatment) *and* time
- For example, if we have a treatment and control group, we can form:

	Before	After	Change
Treatment	Y_{jb}	Y_{ja}	ΔY_j
Control	Y_{kb}	Y_{ka}	ΔY_k

- Why do we want to make a pre-post comparison?

Difference-in-Difference Estimation

- Formally, assume we observe two groups before treatment

$$Y_{jb} = \alpha_j.$$
$$Y_{kb} = \alpha_k.$$

- Later, we observe that only group j received the treatment

$$Y_{ja} = \alpha_j + \delta_t + T, \text{ and } Y_{ka} = \alpha_k + \delta_t$$

- So, if we take the first difference for Y_j, we get:

$$\Delta Y_j = Y_{ja} - Y_{jb} = (\alpha_j - \alpha_j) + \delta_t + T$$

$$\Delta Y_j - \Delta Y_k = T + \delta_t - \delta_t = T.$$

- Difference-in-differences potentially deals with the confounding effect of time


Pennsylvania
Philadelphia
New Jersey
Delaware

Card and Krueger (1994)

TABLE 1—SAMPLE DESIGN AND RESPONSE RATES

	All	Stores in: NJ	Stores in: 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

Card and Krueger (1994)

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

Card and Krueger (1994)

TABLE 2—MEANS OF KEY VARIABLES

Variable	Stores in: NJ	PA	t^{a}
1. *Distribution of Store Types (percentages):*			
a. Burger King	41.1	44.3	−0.5
b. KFC	20.5	15.2	1.2
c. Roy Rogers	24.8	21.5	0.6
d. Wendy's	13.6	19.0	−1.1
e. Company-owned	34.1	35.4	−0.2
2. *Means in Wave 1:*			
a. FTE employment	20.4	23.3	−2.0
	(0.51)	(1.35)	
b. Percentage full-time employees	32.8	35.0	−0.7
	(1.3)	(2.7)	
c. Starting wage	4.61	4.63	−0.4
	(0.02)	(0.04)	
d. Wage = $4.25 (percentage)	30.5	32.9	−0.4
	(2.5)	(5.3)	
e. Price of full meal	3.35	3.04	4.0
	(0.04)	(0.07)	
f. Hours open (weekday)	14.4	14.5	−0.3
	(0.2)	(0.3)	
g. Recruiting bonus	23.6	29.1	−1.0

Card and Krueger (1994)

- What we observe

	Before	After	Δ
NJ	$Y_{N,1992}$	$Y_{N,1993}$	$\Delta Y_N = T + \delta$
PA	$Y_{P,1992}$	$Y_{P,1993}$	$\Delta Y_p = \delta$

- Difference-in-difference estimator (DD):

$$\begin{aligned}\hat{T} &= \Delta Y_N - \Delta Y_P \\ &= T + \delta - \delta \\ &= T\end{aligned}$$

Card and Krueger (1994)

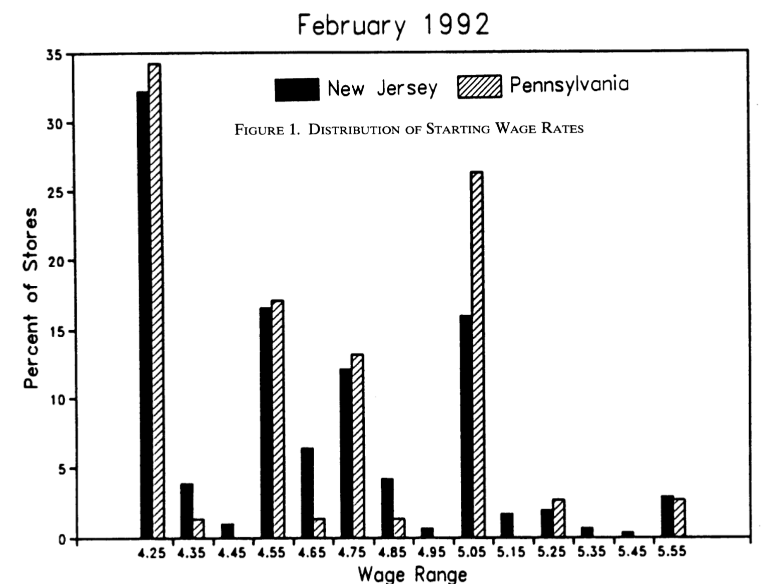
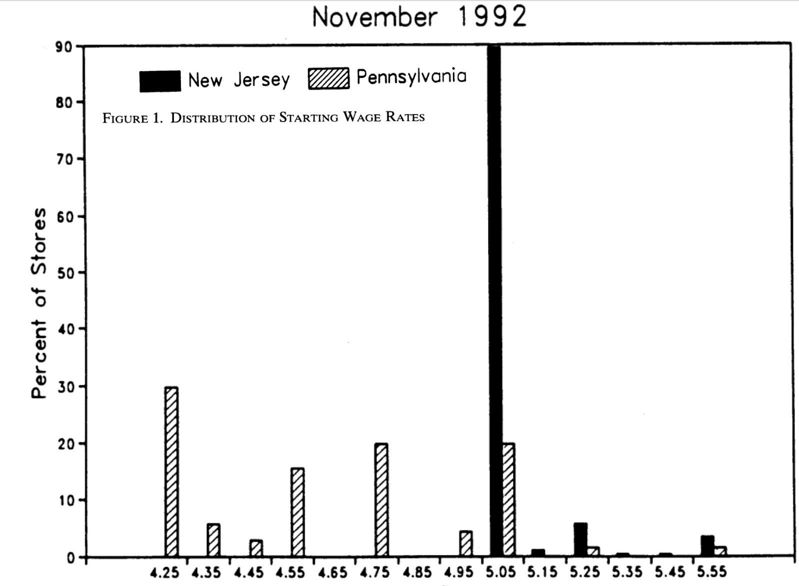


Figure 1. Distribution of Starting Wage Rates

Card and Krueger (1994)



Card and Krueger (1994)

- Table 3 in the paper shows "Per store employment"

	Before	After	Δ
NJ	20.44	21.03	$\Delta Y_n = +0.59$
PA	23.33	21.37	$\Delta Y_p = -2.16$

- Card and Krueger $\hat{T} = 0.59 - (-2.16) = 2.76$ with a standard error of 1.36
  - Therefore, it is statistically significant at the 5 percent level since the t-statistic is ≈ 2.0

Card and Krueger (1994)

Table 3—Average Employment Per Store Before and After the Rise in New Jersey Minimum Wage

Variable	PA (i)	NJ (ii)	Difference, NJ – PA (iii)
	Stores by state		
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)

Interpretations?

Card and Krueger (1994)

Table 3—Average Employment Per Store Before and After the Rise in New Jersey Minimum Wage

Variable	Stores in New Jersey[a] Wage = \$4.25 (iv)	Wage = \$4.26–\$4.99 (v)	Wage ≥ \$5.00 (vi)
1. FTE employment before, all available observations	19.56 (0.77)	20.08 (0.84)	22.25 (1.14)
2. FTE employment after, all available observations	20.88 (1.01)	20.96 (0.76)	20.21 (1.03)
3. Change in mean FTE employment	1.32 (0.95)	0.87 (0.84)	−2.04 (1.14)

Methodology of economics — or why economic theory?

- Positive Economics
  - The study of "what is."
  - Build models to make sense of, and generalize, the phenomena we observe
- Normative Economics
  - Assessing "what ought to be done."

Strengths and Weaknesses

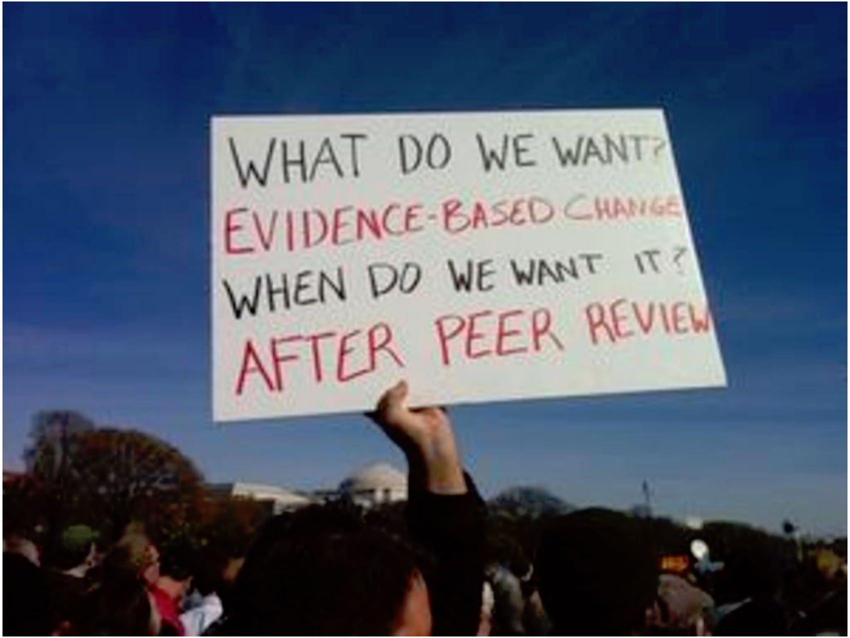
- Strengths
  - *Rigorous* and *internally* consistent
  - *Cohesive*: theory/methods built on first principles
  - *Refutable*: makes strong, testable (refutable) predictions
  - *Practical*: will help you to better understand how the world works.
- Weaknesses
  - "Economics is marked by a startling crudeness in the way it thinks about individuals and their motivations..."— Paul Krugman
  - Strong, simplifying assumptions that are often unpalatable and cannot be completely right

But there are strengths in this weakness

- We have a model of “the world” – and it’s generally too complicated to analyze in its totality, considering all factors at once
- A simplified, highly stylized depiction of the world can be quite helpful
- “The test of the validity of a model is the accuracy of its predictions about real economic phenomena, *not* the realism of its assumptions”—Milton Friedman
- “A hypothesis is important if it explains much by little”—Milton Friedman
- Our approach: simple models, significant insights

Three significant insights of economic approach

1. Economics is about "people doing the best with what they have."
   - We start from the premise that people are *trying* to make the best choices for themselves
2. Equilibrium
   - The market 'aggregates' individual choices to produce collective outcomes—*equilibria*
   - Sometimes equilibria are *spectacularly different* from individual intentions
3. We can evaluate properties of equilibrium using the criterion of efficiency
   - A stunning insight: under some key conditions, the market will produce efficient outcomes
   - And, theory provides insight into why this may or may not occur
   - Moreover, it may provide guidance on how to get to a better outcome
   - 'Market failure' is an opportunity to use economics to address the root of the problem, e.g., bad incentives, externalities, tragedy of the commons, coordination failure, hidden information


WHAT DO WE WANT?
EVIDENCE-BASED CHANGE
WHEN DO WE WANT IT?
AFTER PEER REVIEW