14.03 Micro Theory & Public Policy

Lecture 2. The Minimum Wage Debate and Causal Inference

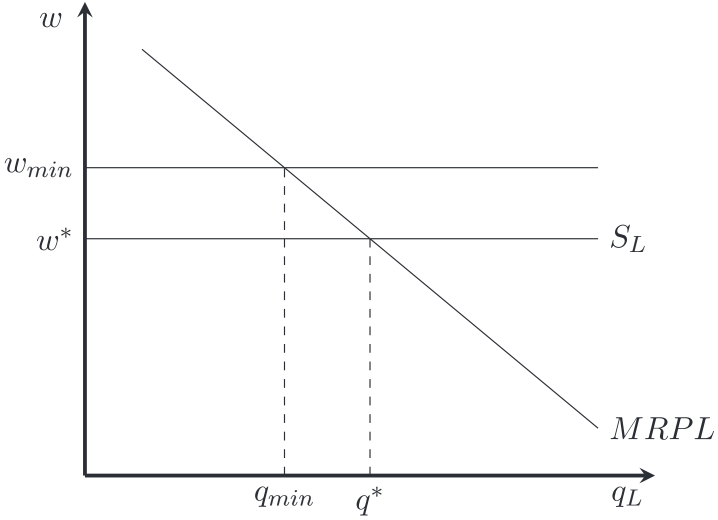
David Autor (Prof), MIT Economics and NBER

Jonathan Cohen (TA), MIT Economics

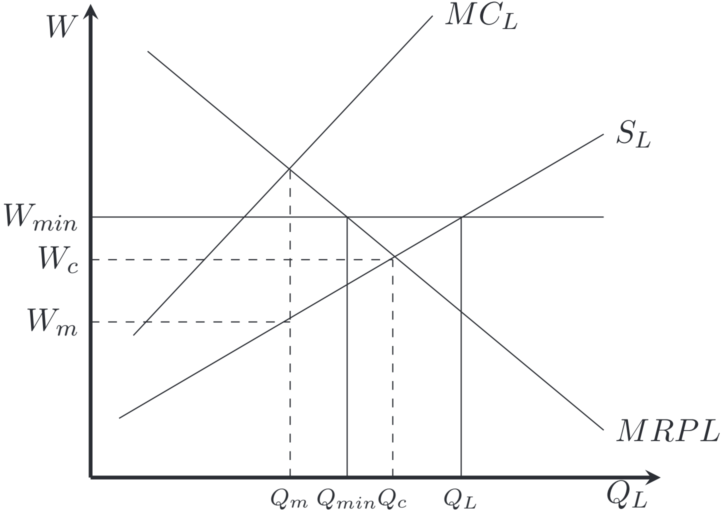
Outline

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.

The minimum wage: competitive labor market

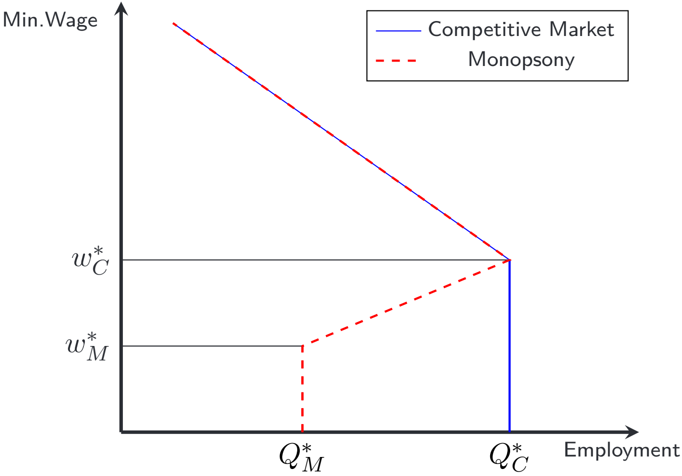


Monopsonistic employer



Effect of a minimum wage

Monopsony vs. competitive market



Testing for monopsony in the labor market

- In the competitive model, an increase in the binding minimum wage always reduces employment: $W \uparrow \rightarrow L \downarrow$
- In the monopsonistic model, an increase in the binding minimum wage (may) raise employment: $W \uparrow \rightarrow L \uparrow$

Poll

Poll: At the time that Card and Krueger (1994) was published, how many academic economists agreed with the following statement: "Do minimum wages substantially lower employment among low-wage workers?"

A: $< 25\%$

B: 25% to 59%

C: 50% to 75%

D: $> 75\%$

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B: 25% to 59%

C: 50% to 75%

D: $> 75\%$ ✓

Changing opinion among economists

Do minimum wages substantially lower employment among low-wage workers?

- **1978** AEA Member Survey: **90%** agreed
- **1992** AEA Member Survey: **72%** agreed
- **2000** AEA Member Survey: **46%** agreed
- **2013** IGM Panel (**$9**/hr): **34%** agreed
- **2015** IGM Panel (**$15**/hr): **26%** agreed

Analysis of petition signers (O'Neill 2014):

Labor economists, recent PhDs *more* likely to support raising minimum wages

Causal Inference

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 incomes tend to be healthier than average — an association

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  - These things could happen, but the correlations are not informative about the causal effects
- Science progresses by analyzing cause and effect — what is 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**

The fundamental problem of causal inference

- Imagine two potential outcomes $\{Y_{0i}, Y_{1i}\}$ for every unit i
- i could be a water molecule, a person, a country, etc.
- The *causal effect* of X on Y is

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

  where T stands for Treatment Effect

- Problem: We observe only

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

  and never observe $Y_{1i} - Y_{0i}$

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

Work-around I: Postulate stability and reversibility

– *Claim:* If the causal effect of X on Y is

  1. *Temporally Stable:* the same at every point in time, and
  2. *Reversible:* Undoing the cause reverses the effect

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

  then we can observe $Y_{1i} - Y_{0i}$ by repeatedly changing X from 0 to 1

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- Issues

    - Temporal stability and causal transience cannot be tested
    - And these assumptions may not always be plausible

- Examples/Counter-examples:

    - Water from ice to steam and back
    - Treatment for high cholesterol for patient i

Work-around II: Postulate unit homogeneity

- If Y_{1i} and Y_{0i} are identical for all i, so $Y_{1i} = Y_1 \,\forall\, i$ and $Y_{0i} = Y_0 \,\forall\, i$
- Then, causal effect of X on Y is simply difference $Y_{1i} - Y_{0j}$ for $i \neq j$
- Examples/Counter-examples:
  - Water molecules
  - Treatment for high cholesterol for patient i
- Only plausible under certain laboratory conditions

Work-around III: Estimate causal effects for populations rather than individuals

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

- *Must therefore acknowledge that we cannot estimate*

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

- Instead settle for population effects

Estimating Average Treatment Effect

Average Treatment Effect on the Treated:

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

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

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

- Is this a good idea?

Estimating ATT

- Want to identify a set of treatment/control people for whom the *counterfactual* outcomes are comparable

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- *Treatment-Control Balance:*

$$E\left[Y_1|X=1\right]=E\left[Y_1|X=0\right] \tag{1}$$
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- 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.

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- If treatment and control groups are balanced, we can say that assignment to treatment is *ignorable*
  - You could swap the treatment and control groups (before the experiment) and get the same treatment effect estimate (on average).

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\end{aligned} \tag{2}
$$

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

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

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

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

Estimating ATT

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

$$E\left[Y_1|X=1\right] \lesseqgtr E\left[Y_1|X=0\right]?$$
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- In the cholesterol example, it is natural that treatment-control balance will be violated:

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- 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

- Suppose we're interested in effect of attending MIT on math knowledge
  - Randomly assigned half of qualified MIT applicants to $MIT = 1$ and half to $MIT = 0$
- Randomization guarantees that

$$\begin{aligned} E\left[Y_1 | MIT = 1\right] &= E\left[Y_1 | MIT = 0\right] \\ E\left[Y_0 | MIT = 1\right] &= E\left[Y_0 | MIT = 0\right]. \end{aligned}$$

- Therefore, Treatment-Control Balance should be satisfied
- Now, consider

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

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

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

- ATT and ATE are distinct

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]

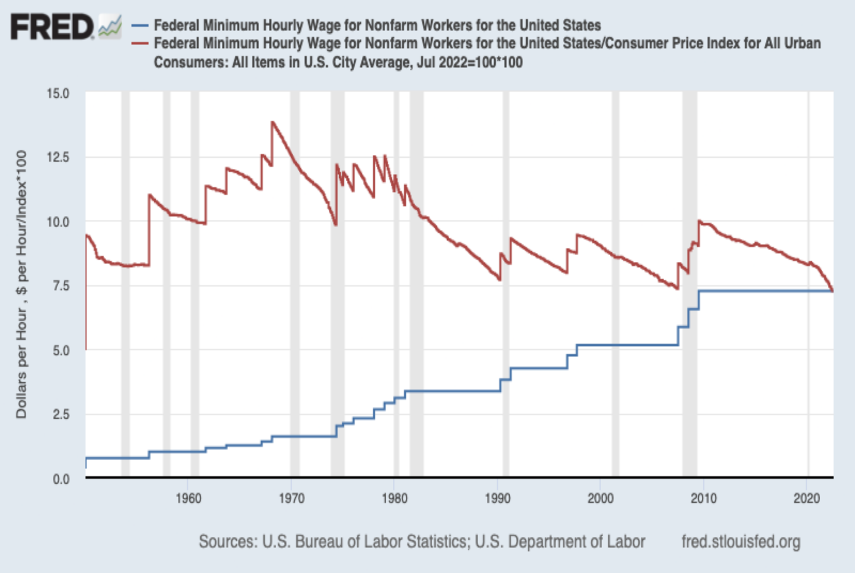
The Quintessential Quasi-Experiment: Vietnam Draft Lottery

"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)

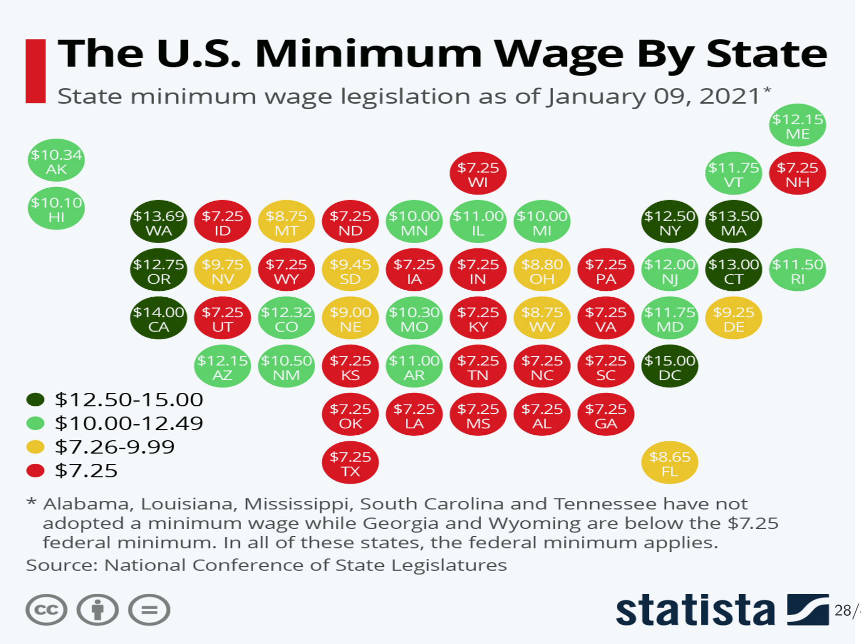
Vietnam Random Number Draft Lottery Sequence in 1972

	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

Nominal and Real Value of Federal Minimum Wage, 1950–2022



Dramatic Differences in State Minimum Wage Floors (2021)




Pennsylvania
Philadelphia
New Jersey
Delaware

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

Difference-in-Difference Estimation Graphically

Card & Krueger (1994)

	Before	After	Δ
NJ	$Y_{n,1992}$	$Y_{n,1993}$	ΔY_n
PA	$Y_{p,1992}$	$Y_{p,1993}$	ΔY_p

– This suggests:

$$\hat{T} = \Delta Y_n - \Delta Y_p$$

Card & 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 & 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 & 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
	(2.3)	(5.1)	

Card & Krueger (1994)

TABLE 2—MEANS OF KEY VARIABLES

Variable	Stores in: NJ	PA	t[a]
3. *Means in Wave 2:*			
a. FTE employment	21.0	21.2	−0.2
	(0.52)	(0.94)	
b. Percentage full-time employees	35.9	30.4	1.8
	(1.4)	(2.8)	
c. Starting wage	5.08	4.62	10.8
	(0.01)	(0.04)	
d. Wage = \$4.25 (percentage)	0.0	25.3	—
		(4.9)	
e. Wage = \$5.05 (percentage)	85.2	1.3	36.1
	(2.0)	(1.3)	
f. Price of full meal	3.41	3.03	5.0
	(0.04)	(0.07)	
g. Hours open (weekday)	14.4	14.7	−0.8
	(0.2)	(0.3)	
h. Recruiting bonus	20.3	23.4	−0.6
	(2.3)	(4.9)	

Card & Krueger (1994)

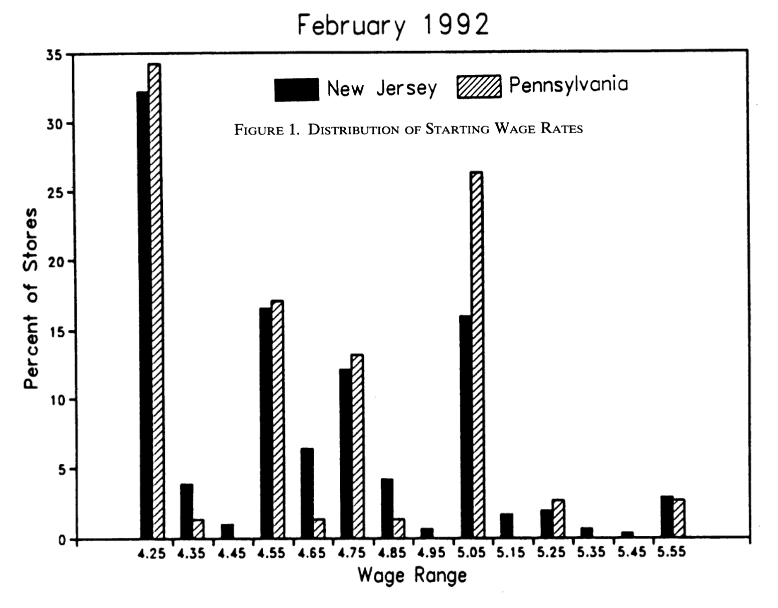
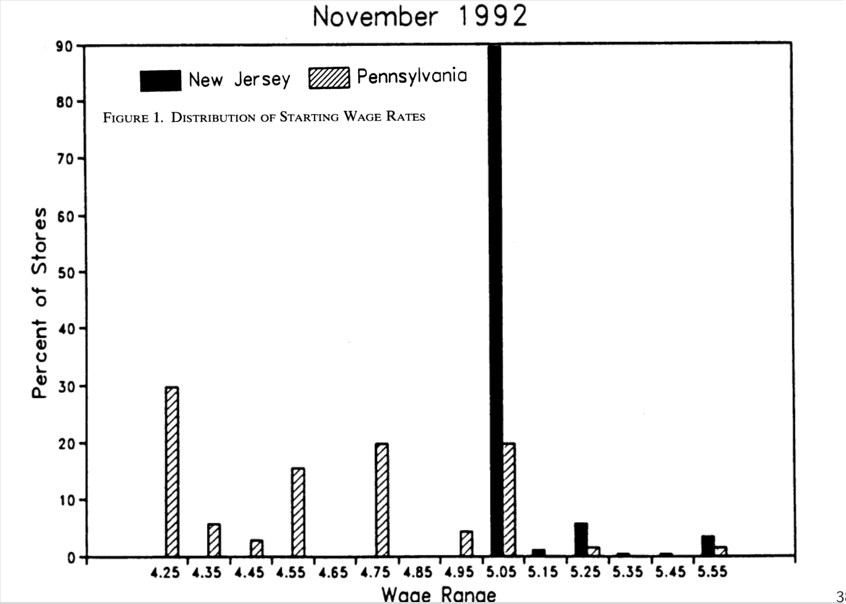


FIGURE 1. DISTRIBUTION OF STARTING WAGE RATES

Card & Krueger (1994)



Card & 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	21.17	$\Delta Y_p = -2.16$

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

Card & Krueger (1994)

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

	Stores by state		
Variable	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)

Interpretations

1. Monopsony

Interpretations

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2. What else?

Card & Krueger (1994)

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

	Stores in New Jersey[a]		
Variable	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)

Poll: Based on the evidence you've seen, what minimum wage policy would you recommend for the U.S.?

A: No national minimum wage

B: National minimum wage, Congress decides

C: National minimum wage, indexed to Consumer Price Index or median wage

D: Other

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.

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- 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
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- 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

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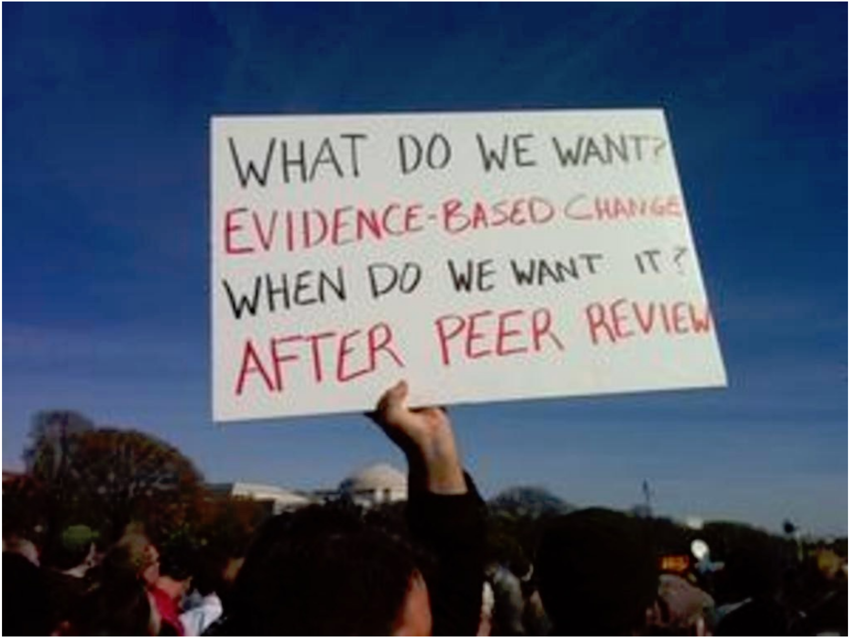
   - We start from the premise that people are *trying* to make the best choices for themselves
2. Equilibrium
   - The market 'aggregates' individual choices to produce collective outcomes—*equilibria*
   - Sometimes equilibria are *spectacularly different* from individual intentions
3. We can evaluate 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