Survey Research and Design

Panel Surveys

William Marble

November 28, 2023

The Timing of Surveys

Most surveys capture attitudes at a single point in time

- E.g., the Census's American Community Survey measures household and personal attributes at a single point in the year

The Timing of Surveys

Most surveys capture attitudes at a single point in time

- E.g., the Census's American Community Survey measures household and personal attributes at a single point in the year

But surveys are also useful for measuring over-time change

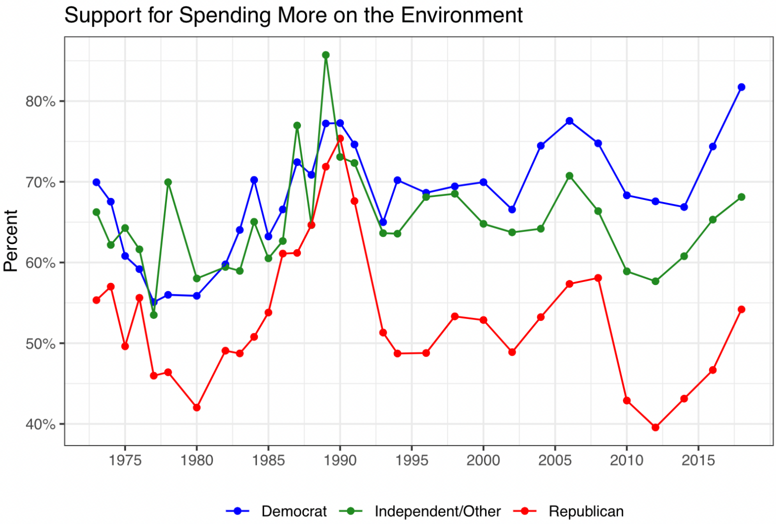
- E.g., changing attitudes toward gay rights or towards environmental issues; changes in polling throughout an election cycle; changes in income over time

Goals for Over-Time Inference

Description: how does a population-level quantity of interest change over time?

Goals for Over-Time Inference

Description: how does a population-level quantity of interest change over time?



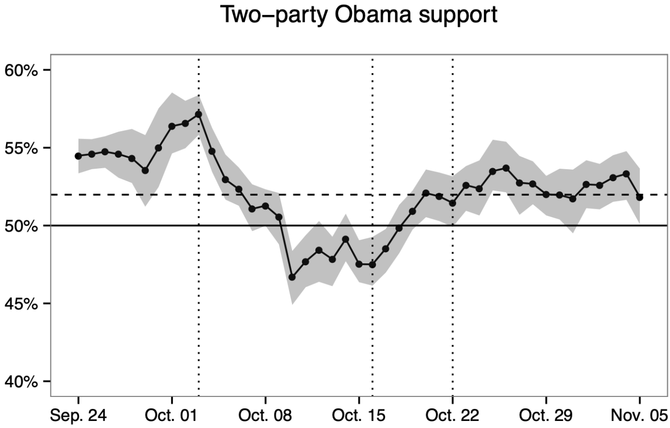
Source: General Social Survey

Goals for Over-Time Inference

Causal inference: how does some event (a.k.a. treatment, intervention) affect an outcome of interest?

Goals for Over-Time Inference

Causal inference: how does some event (a.k.a. treatment, intervention) affect an outcome of interest?



Vertical lines indicates timing of presidential debates

Source: Gelman et al. (2016)

Obtaining Valid Descriptive Inference

For valid over-time *description*: **comparability** across surveys

- comparable sample: draw from the same population, ensure that differential nonresponse is constant across samples
- comparable measures: ask same question(s)

Obtaining Valid Causal Inference

For valid *causal inference*: need an **identification strategy** in addition to comparable samples and outcomes

- a set of assumptions that enables you to infer the **counterfactual** outcomes
- causal inference answers the question: "How would outcomes have been different if X had occurred instead of Y?"
- need to find some way of estimating what would have happened under Y
- often involves finding a **control group**

Analogy: Want a design that approximates a randomized experiment.

Two Flavor of Over-Time Surveys

- **Panel survey**: repeated observation of *the same respondents* (a.k.a. **longitudinal survey**)

Two Flavor of Over-Time Surveys

- **Panel survey**: repeated observation of *the same respondents* (a.k.a. **longitudinal survey**)
- **Rolling cross-section**: the same (or similar) survey conducted over time with a *new sample* drawn from the same population

Other Terminology for Over-Time Surveys

- **Survey wave**: a set of interviews conducted around a particular time. Panel and rolling cross-section surveys always have at least two waves

Other Terminology for Over-Time Surveys

- **Survey wave**: a set of interviews conducted around a particular time. Panel and rolling cross-section surveys always have at least two waves
- **Attrition**: in a panel survey, when a unit responds to one wave of a survey but does not respond to subsequent waves

Panel Surveys

- Panel surveys are useful because they ensure comparability in the sample
- Enables examination of change at the individual level, rather than in aggregate
- Especially useful for causal inference
- Allows us to "control for" some individual-level characteristics that we can't directly observe $\rightsquigarrow$ stronger claims to **internal validity**

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

- Cross-sectional evidence: do states with higher minimum wages have higher unemployment?

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

- Cross-sectional evidence: do states with higher minimum wages have higher unemployment?
  - could be confounded: e.g., maybe stronger economy $\rightsquigarrow$ lower unemployment and higher minimum wage

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

- Cross-sectional evidence: do states with higher minimum wages have higher unemployment?
  - could be confounded: e.g., maybe stronger economy $\rightsquigarrow$ lower unemployment and higher minimum wage
- Over-time evidence: does unemployment go up after minimum wage increases?

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

- Cross-sectional evidence: do states with higher minimum wages have higher unemployment?
  - could be confounded: e.g., maybe stronger economy $\rightsquigarrow$ lower unemployment and higher minimum wage
- Over-time evidence: does unemployment go up after minimum wage increases?
  - could be over-time confounding: e.g., workers lobby for higher minimum wage when they know economy will be good for a few years
  - more generally, many things affect employment levels $\rightsquigarrow$ might confuse effect of macro-economic conditions with minimum wage change

Does the Minimum Wage Lead to Higher Unemployment?

Prediction from simple economic theory of labor markets (perfect competition): increase in minimum wage $\rightsquigarrow$ decreased employment.

How could this theory be tested in the real world?

- Cross-sectional evidence: do states with higher minimum wages have higher unemployment?
    - could be confounded: e.g., maybe stronger economy $\rightsquigarrow$ lower unemployment and higher minimum wage
- Over-time evidence: does unemployment go up after minimum wage increases?
    - could be over-time confounding: e.g., workers lobby for higher minimum wage when they know economy will be good for a few years
    - more generally, many things affect employment levels $\rightsquigarrow$ might confuse effect of macro-economic conditions with minimum wage change
- Other ideas?

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

By David Card and Alan B. Krueger*

Card and Krueger (1994): Setup

- New Jersey passed a law increasing minimum wage from \$4.25/hr (federal) to \$5.05/hr (state level)
- New MW took effect in April 1992
- Card and Krueger (1994) use this change to study the effect on employment
- Focus on employment in fast-food restaurants in New Jersey $\rightsquigarrow$ many minimum-wage workers, expected to be affected by change in law
- Used surveys to measure wages and employment at individual fast-food restaurants

Card and Krueger (1994): Identification Strategy

- Need to compare actual employment rate in NJ fast food after MW change with the **counterfactual** employment rate in NJ fast food had the MW not changed

Card and Krueger (1994): Identification Strategy

- Need to compare actual employment rate in NJ fast food after MW change with the **counterfactual** employment rate in NJ fast food had the MW not changed
- How to impute this counterfactual?

Card and Krueger (1994): Identification Strategy

- Need to compare actual employment rate in NJ fast food after MW change with the **counterfactual** employment rate in NJ fast food had the MW not changed
- How to impute this counterfactual?
- Solution: construct a survey panel of fast food restaurants in both NJ and Pennsylvania
- **Assumption**: PA fast food restaurants are affected by similar labor market dynamics as those in NJ, but do not face a change in MW

Card and Krueger (1994): Intuition

- Measure store-level change in employment before and after change in law (in both PA and NJ)
- If the average store in NJ loses more employees after the MW increases than the average PA store, evidence that MW decreases employment

Card and Krueger (1994): Sample

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
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

[a]Stores with working phone numbers only; 29 stores in original sample frame had disconnected phone numbers.

[b]Includes one store closed because of highway construction and one store closed because of a fire.

[c]Includes 371 phone interviews and 28 personal interviews of stores that refused an initial request for a phone interview.

Card and Krueger (1994): Results

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)
4. Change in mean FTE employment, balanced sample of stores[c]	−2.28 (1.25)	0.47 (0.48)	2.75 (1.34)
5. Change in mean FTE employment, setting FTE at temporarily closed stores to 0[d]	−2.28 (1.25)	0.23 (0.49)	2.51 (1.35)

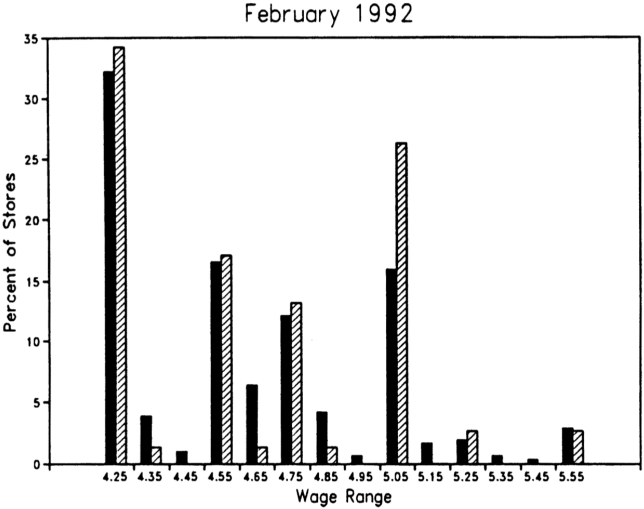
(FTE = full-time equivalent employees)

Card and Krueger (1994): Potential Critiques

Maybe PA and NJ stores are not comparable?

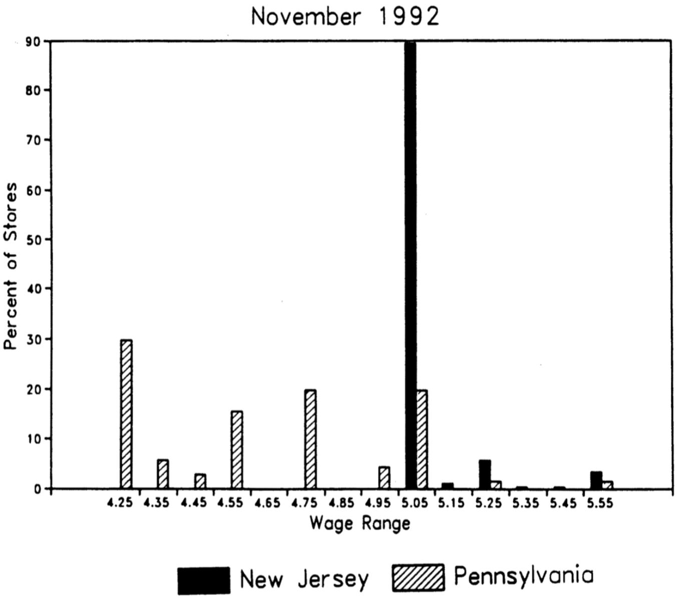
Card and Krueger (1994): Potential Critiques

Maybe PA and NJ stores are not comparable?



Solid = NJ, Stripe = PA

Card and Krueger (1994): Comparison of Starting Wages in PA and NJ



Card and Krueger (1994): Comparability of Stores

TABLE 2—MEANS OF KEY VARIABLES

Variable	Stores in: NJ	Stores in: 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)	
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)	

Notes: See text for definitions. Standard errors are given in parentheses.
[a]Test of equality of means in New Jersey and Pennsylvania.

Card and Krueger (1994): Other Critiques?

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?
- Maybe fast food restaurants in NJ *anticipated* the change and laid off workers before the baseline survey?

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?
- Maybe fast food restaurants in NJ *anticipated* the change and laid off workers before the baseline survey?
- Maybe some stores shut down in NJ?

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?
- Maybe fast food restaurants in NJ *anticipated* the change and laid off workers before the baseline survey?
- Maybe some stores shut down in NJ?
  - some evidence of this; result is robust to imputing 0 employment for these stores

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?
- Maybe fast food restaurants in NJ *anticipated* the change and laid off workers before the baseline survey?
- Maybe some stores shut down in NJ?
  - some evidence of this; result is robust to imputing 0 employment for these stores
- Maybe the stores that respond to the second-wave survey are different than those that don't (*panel attrition*)?

Card and Krueger (1994): Other Critiques?

- Maybe something else changed just in NJ at the same time as the minimum wage?
- Maybe fast food restaurants in NJ *anticipated* the change and laid off workers before the baseline survey?
- Maybe some stores shut down in NJ?
  - some evidence of this; result is robust to imputing 0 employment for these stores
- Maybe the stores that respond to the second-wave survey are different than those that don't (*panel attrition*)?
  - relatively little attrition $\rightsquigarrow$ 9 attempts to reach the store
  - robust to including just those stores that answered both waves

General Methodology: Difference-in-Differences

- A method of causal inference where we compare changes over time among a **treated** group and a **control** group
- Find some units that are affected by treatment (e.g., changing minimum wage) and those that are not

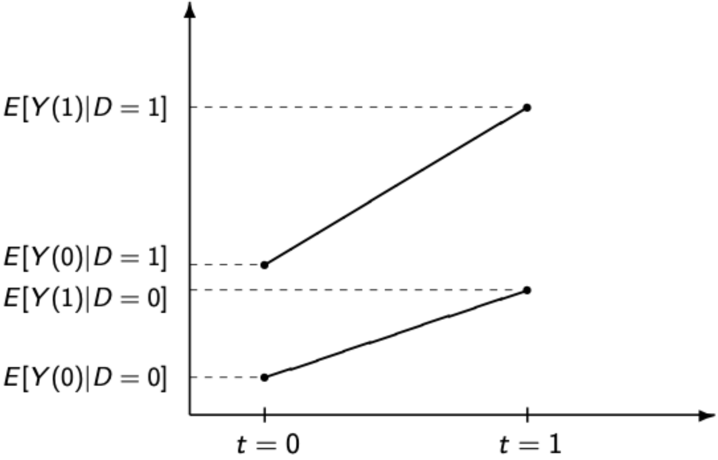
General Methodology: Difference-in-Differences

- A method of causal inference where we compare changes over time among a **treated** group and a **control** group
- Find some units that are affected by treatment (e.g., changing minimum wage) and those that are not
- Compare before-after difference in outcomes across groups
  - Find average difference before/after in treated group, Δ_t
  - Find average difference before/after in control group, Δ_c
  - Treatment effect estimate: difference in those differences: $\Delta_t - \Delta_c$

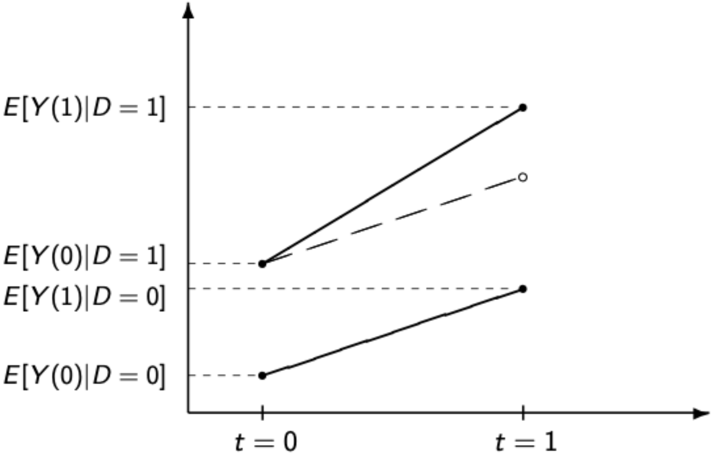
General Methodology: Difference-in-Differences

- A method of causal inference where we compare changes over time among a **treated** group and a **control** group
- Find some units that are affected by treatment (e.g., changing minimum wage) and those that are not
- Compare before-after difference in outcomes across groups
    - Find average difference before/after in treated group, Δ_t
    - Find average difference before/after in control group, Δ_c
    - Treatment effect estimate: difference in those differences: $\Delta_t - \Delta_c$
- Key assumption: **parallel trends**
    - Absent treatment, the change in the treatment group *would have been the same* as the change in the control group

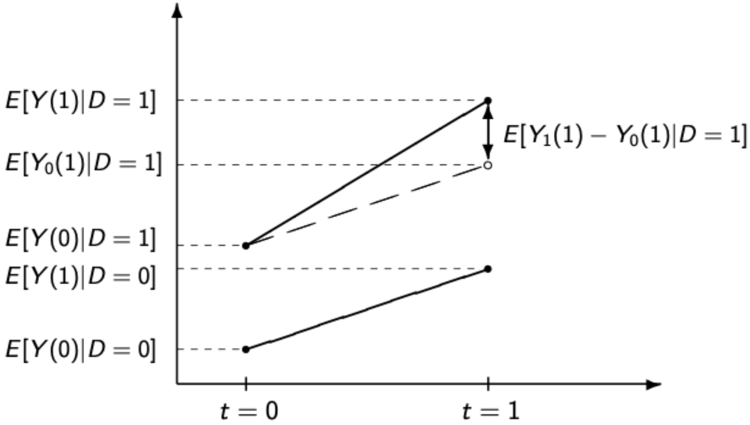
Observed data:



Parallel trends assumption:



Treatment effect estimate:



Parallel Trends, Assumptions

- Can't directly validate because it is an assumption on counterfactuals
- If multiple waves before treatment: see if the treatment and control groups are trending together
- Substantive knowledge is important: are ther other things happening at the same time?

How Does the Media Affect Voting Behavior?

Voters often consume ideologically like-minded media:

- Fox News viewers usually vote for Republicans
- MSNBC viewers usually vote for Democrats

How Does the Media Affect Voting Behavior?

Voters often consume ideologically like-minded media:

- Fox News viewers usually vote for Republicans
- MSNBC viewers usually vote for Democrats

Do news media *affect* viewers' political stances and behavior?

How could you use panel data to test for the causal effect of news media on political views?

Ladd and Lenz investigate a shift in political endorsements by *The Sun* between the 1992 and 1997 elections in the U.K.


THE Sun

MAY 1st

An historic announcement from Britain's No1 newspaper

THE PAPER OF THE PEOPLE

THE SUN BACKS BLAIR

Give change a chance


ELECTION Sun

MAY 1 POLLING DAY

IT MUST BE YOU

PAGE ONE OPINION

The Sun

- *The Sun*, a tabloid, is one of the largest newspapers in the U.K.
- Has a conservative slant: owned by Rupert Murdoch (owner of Fox News, the *Wall Street Journal*, and the *New York Post*)
- Amid economic woes in the mid-1990s, *The Sun* decided to endorse Tony Blair's Labour Party in the 1997 elections
- Rare chance to assess the effect of endorsements on voting behavior

Ladd and Lenz: Data

Data comes from the British Election Panel Study

- Interviewed the same respondents five times from 1992-1996 and once after the 1997 election
- Includes questions about media consumption, political attitudes, and voting behavior

Ladd and Lenz: Data

Data comes from the British Election Panel Study

- Interviewed the same respondents five times from 1992-1996 and once after the 1997 election
- Includes questions about media consumption, political attitudes, and voting behavior

Measurement

- Outcome variable: support for the Labour Party
- Treatment group: those who read *The Sun* (or another "switching" paper) in 1996
- Control group: those who read a nonswitching paper or did not read a paper

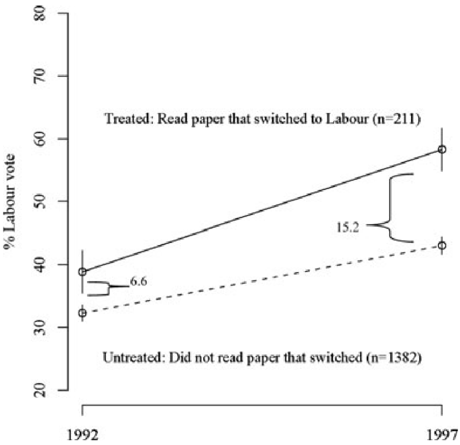
Ladd and Lenz: Analysis Strategy

How should Ladd and Lenz analyze the data?

Ladd and Lenz: Analysis Strategy

How should Ladd and Lenz analyze the data?

FIGURE 1 Persuasive Effect of Endorsement Changes on Labour Vote Choice between 1992 and 1997



Ladd and Lenz: Threats to Validity

What is the key assumption?

Ladd and Lenz: Threats to Validity

What is the key assumption?

Parallel trends: without the shift in endorsement, increase in Labour vote share would have been the same for readers of switching papers as for everyone else.

Ladd and Lenz: Threats to Validity

What is the key assumption?

Parallel trends: without the shift in endorsement, increase in Labour vote share would have been the same for readers of switching papers as for everyone else.

Potential violations of this assumption?

Ladd and Lenz: Threats to Validity

What is the key assumption?

Parallel trends: without the shift in endorsement, increase in Labour vote share would have been the same for readers of switching papers as for everyone else.

Potential violations of this assumption?

- both newspapers and readers influenced by the same events
- readers' shift in preferences influencing newspaper endorsements

Ladd and Lenz: Threats to Validity

What is the key assumption?

Parallel trends: without the shift in endorsement, increase in Labour vote share would have been the same for readers of switching papers as for everyone else.

Potential violations of this assumption?

- both newspapers and readers influenced by the same events
- readers' shift in preferences influencing newspaper endorsements

How to probe the plausibility of this assumption?

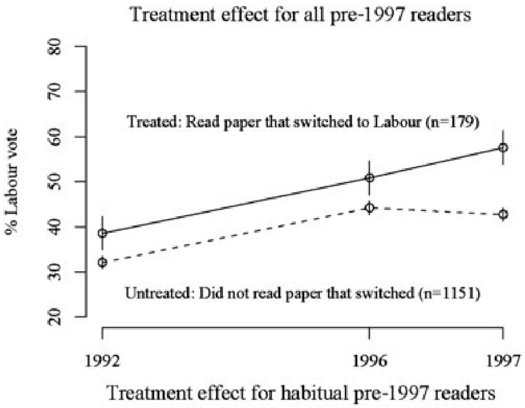
Ladd and Lenz: Robustness Checks

Check for plausibility of parallel trends by using multiple "pre-treatment" outcomes $\rightsquigarrow$ if treatment and control groups started to diverge before treatment, suggests parallel trends assumption is violated.

Ladd and Lenz: Robustness Checks

Check for plausibility of parallel trends by using multiple "pre-treatment" outcomes $\rightsquigarrow$ if treatment and control groups started to diverge before treatment, suggests parallel trends assumption is violated.

FIGURE 2 **The Treatment Effect Only Emerges in 1997**



Ladd and Lenz: Attrition

Panel attrition could also threaten inference

Ladd and Lenz: Attrition

Panel attrition could also threaten inference

- Perhaps conservative readers of *The Sun* became less likely to answer the follow-up survey in 1997
- In that case, would overstate the treatment effect: we just don't observe the people who didn't change their opinions

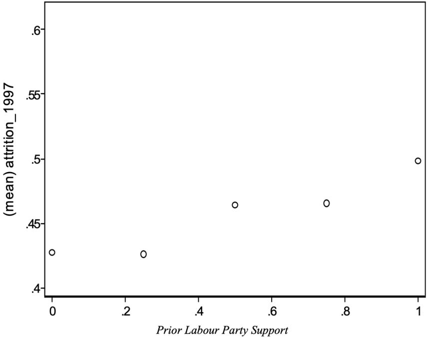
Ladd and Lenz: Attrition

Panel attrition could also threaten inference

- Perhaps conservative readers of *The Sun* became less likely to answer the follow-up survey in 1997
- In that case, would overstate the treatment effect: we just don't observe the people who didn't change their opinions

Ladd and Lenz test this by looking at attrition by 1992 vote choice:

Figure 3S: Attrition rate between 1992 and 1997 by Support for Labour Party in 1992



Panel Data Summary and Diff-in-Diff Summary

- Panel data can be useful for causal inference, particularly when paired with a difference-in-differences design
- Key advantage: we don't need treatment and control groups to be *the same*, only that they would exhibit *parallel trends* in the absence of treatment
- If panel data is unavailable but rolling cross-section is, can also use diff-in-diff
  - caveat: need to be able to objectively identify treatment and control groups
  - difficulty arises if the treatment affects measurement of who is in the treatment group
  - e.g., if Labour endorsement led liberals to read *The Sun*, couldn't reliably identify the treatment group *at the time of the treatment*

Estimating the Effect of Treatments that Affect All Units

Last Time: Panel Data

Panel data

Last Time: Panel Data

Panel data

- Repeated observations of the same units
- Allows observation of both cross-sectional and temporal variation
- Useful for estimating causal effects (a.k.a. treatment effects) using difference-in-differences
- Key idea: some units are treated while others aren't

Estimating the Effect of Treatments that Affect Everyone

Panel data (or rolling cross-section data) is useful for causal inference if you can reliably identify treatment and control groups.

Estimating the Effect of Treatments that Affect Everyone

Panel data (or rolling cross-section data) is useful for causal inference if you can reliably identify treatment and control groups.

But what if *everyone* is exposed to the treatment?

Estimating the Effect of Treatments that Affect Everyone

Panel data (or rolling cross-section data) is useful for causal inference if you can reliably identify treatment and control groups.

But what if *everyone* is exposed to the treatment?

- no control group $\rightsquigarrow$ can't use diff-in-diff or other methods
- is it possible to estimate the effect of widespread events?

What can be done instead?

Estimating the Effect of Treatments that Affect Everyone

Panel data (or rolling cross-section data) is useful for causal inference if you can reliably identify treatment and control groups.

But what if *everyone* is exposed to the treatment?

- no control group $\rightsquigarrow$ can't use diff-in-diff or other methods
- is it possible to estimate the effect of widespread events?

What can be done instead?

Unexpected Events During Survey Administration

- *Unexpected events* may present an opportunity for causal inference
- If we survey people directly before and directly after an unexpected event, differences in responses may be caused by the event itself
- Intuition: whether someone gets surveyed just before or just after the event is essentially random $\leadsto$ "before" and "after" respondents should be the same on other attributes
- Research strategy: find a survey that just happened to be in the field during an unexpected event and compare responses

Hofstetter (1969): The Immediate Aftermath of MLK's Assassination

- How did the assassination of Martin Luther King affect attitudes toward the political system?
- Hofstetter suggests that Black Americans may have disengaged from the political system, as he provided a (symbolic and political) link between a marginalized community and those with political power
- But this is hard to test:
  - everyone was exposed to MLK's assassination $\rightsquigarrow$ no control group
  - many things changed soon after the assassination $\rightsquigarrow$ hard to isolate the effect of the assassination itself

Hofstetter: Research Strategy

- A public opinion survey was being conducted in early April 1968 in central Ohio
- In the evening of April 4, media outlets reported news of MLK's assassination
- Hofstetter compares "affective" attitudes toward various political groups among those interviewed before and after the assassination $\rightsquigarrow$ whether respondents feel positively or negatively
- Disengagement hypothesis: more negative affect toward mainstream political institutions and actors

Hofstetter (1969): Results

Race	Political Object	Before	After	Difference
White	Police	87.9%	86.5%	−1.4
Black		88.9	58.6	−30.3
White	Whites	81.9	79.5	−2.4
Black		70.4	51.7	−18.7
White	Dem. Party	68.7	67.3	−1.4
Black		77.8	86.2	8.4
White	LBJ	54.9	57.1	2.2
Black		73.1	75.9	2.8
White	Rep. Party	69.2	72.4	3.2
Black		48.1	35.6	−12.5
White	Nixon	64.3	62.8	−1.5
Black		59.3	31.0	−28.3

Positive Affect Before and After MLK Assassination

Threats to Inference

What threats to internal validity might there be in this design?

Threats to Inference

What threats to internal validity might there be in this design?

Small sample size

- White respondents: 182 before, 156 after
- Black respondents: 27 before, 29 after

Threats to Inference

What threats to internal validity might there be in this design?

Small sample size

- White respondents: 182 before, 156 after
- Black respondents: 27 before, 29 after
- Check covariate balance before/after

Threats to Inference

What threats to internal validity might there be in this design?

Small sample size

- White respondents: 182 before, 156 after
- Black respondents: 27 before, 29 after
- Check covariate balance before/after

Differential nonresponse before/after treatment

- Respondents might not respondent *because* of treatment
- Which way is this likely to bias results?

Threats to Inference

What threats to internal validity might there be in this design?

Small sample size

- White respondents: 182 before, 156 after
- Black respondents: 27 before, 29 after
- Check covariate balance before/after

Differential nonresponse before/after treatment

- Respondents might not respondent *because* of treatment
- Which way is this likely to bias results?

Concurrent events

- Could misattribute change to the wrong event
- Unlikely in this case

Effects of U.S. Withdrawal from Afghanistan on Attitudes Toward U.S.

What was the effect of the chaotic American withdrawal from Afghanistan on attitudes toward the U.S.?

Effects of U.S. Withdrawal from Afghanistan on Attitudes Toward U.S.

What was the effect of the chaotic American withdrawal from Afghanistan on attitudes toward the U.S.?

U.S. withdrew from Afghanistan in August 2021 after Taliban rapidly took control of the country.

Chaotic evacuation and airlift from Kabul airport after fall of Kabul on August 15

Effect on Perceptions of U.S.


FINANCIAL TIMES

Opinion **Afghanistan**

Joe Biden's credibility has been shredded in Afghanistan

But the fall of the country to the Taliban would also create a dilemma for China


FOREIGN AFFAIRS

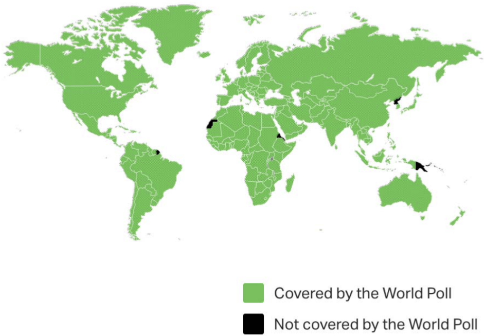
American Credibility After Afghanistan

What the Withdrawal Really Means for Washington's Reputation

By Joshua D. Kertzer **September 2, 2021**

Examining this Empirically

Gallup World Poll: "Initiative to Measure the Will of Every Person on Earth"



In August 2021, there were 21 countries with surveys in the field.

Key outcome measure: Approval of the "the job performance of the leadership of the United States"

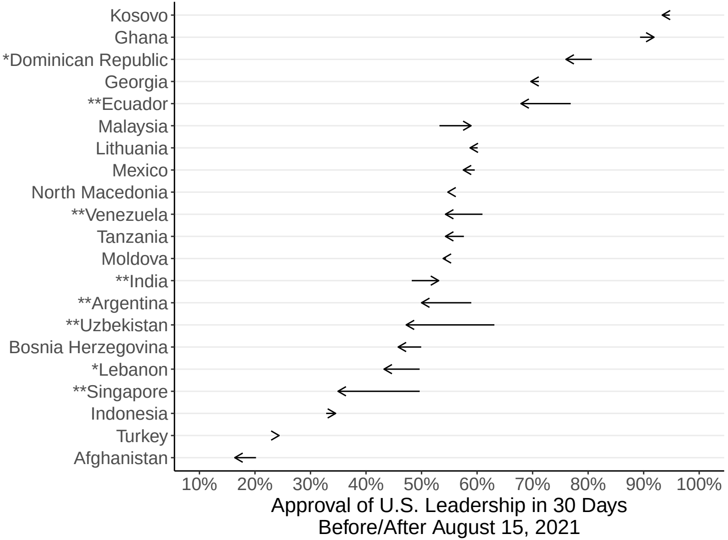
Design

Is there a decrease in approval of U.S. leadership in the wake of the Afghanistan withdrawal? If so, is there spillover to perceptions of U.S. allies?

We use an unexpected event survey design to look at this question.

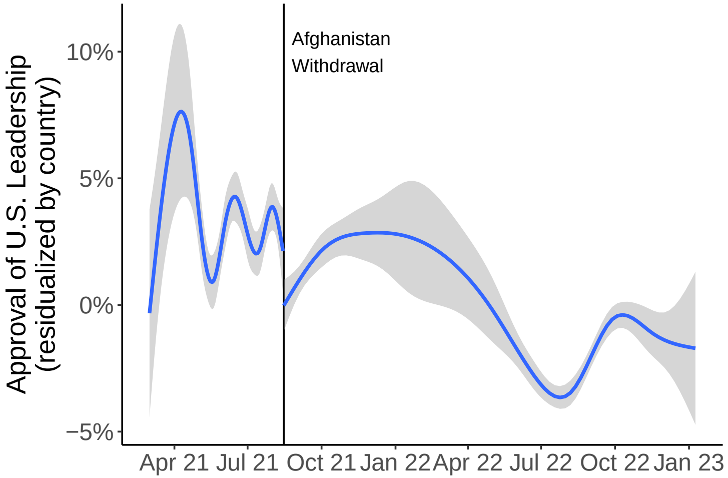
Compare attitudes toward U.S. before/after withdrawal.

Raw Data: Change

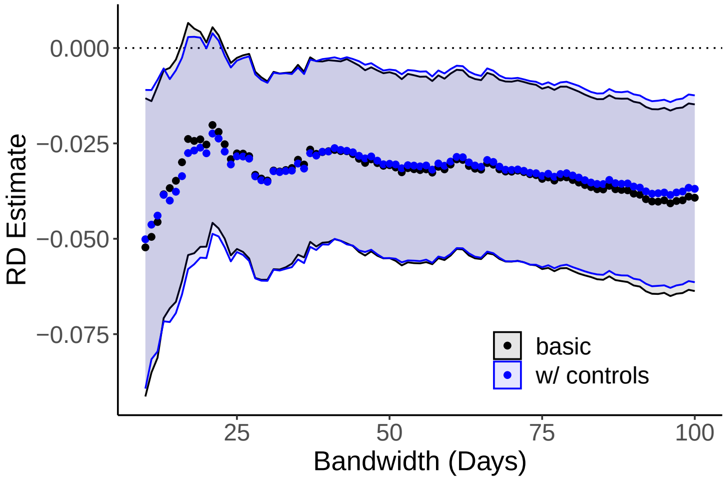


Time Series

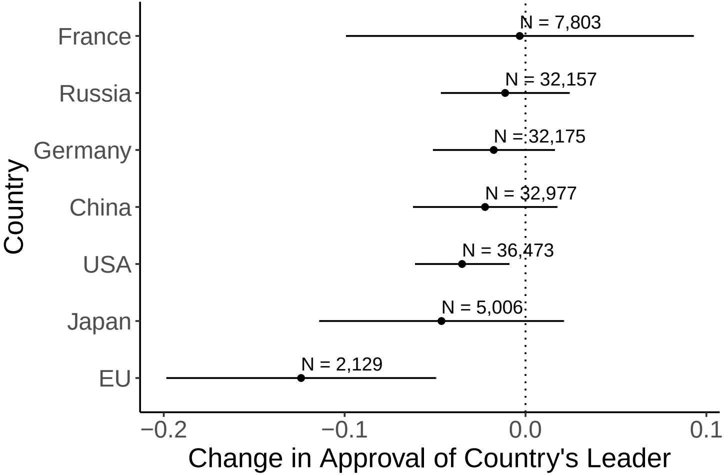
Outcome: Share of respondents who approve of U.S. leadership, accounting for country-level averages.



How Much Does the Time Frame Matter?



Spillover to Other Countries?



Preliminary Summaries

Findings

- See a significant decrease in approval of U.S. leadership after Afghanistan withdrawal
- Some evidence spillovers to other countries (E.U. in particular)
- No "zero-sum" effect: China/Russia attitudes don't improve

Limitations and Extensions

- Weird set of countries in sample
- Can't examine *credibility* per se — just "approval" of leadership

Summing Up

- Over-time data is useful for measuring trends
- For many social science applications, also enables us to use causal inference tools to study the effect of events on attitudes and behavior
- Panel data is ideal, but possible to come up with research designs even in the absence of panel data using "unexpected events"