POLI210: Political Science Research Methods

Lecture 4.2: Experiments and Quasi-Experiments

Olivier Bergeron-Boutin

September 28th, 2021

Boring admin stuff

- Assignment 2 is out – start early!
    - Post questions on discussion board (error messages helpful)
- RMarkdown video
- Grades for assignment 1 are out
- TEAM mentors

The problem

If we allow units to **self-select** into the treatment, we end up with a problem

- The units that choose the treatment are systematically different
  - People go to the hospital because, if they didn't, they would be very sick
  - Students come to OHs because they're interested in the content
    - If they didn't come to OHs (counterfactual), they would probably do well regardless
- In terms of POs...
  - The potential outcome under control for those who self-selected into the treatment is different, on average, than the potential outcome under control for those who self-selected into the control

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
    - By "decide" we mean: randomly choose who gets treatment

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
    - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
  - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?
- It solves the selection bias

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
  - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?
- It solves the selection bias
  - On average, treated and control units should be very similar

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
  - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?
- It solves the selection bias
  - On average, treated and control units should be very similar
  - Intuitively: there is nothing dissimilar between the treated and control units, *except* for the application of treatment

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
    - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?
- It solves the selection bias
    - On average, treated and control units should be very similar
    - Intuitively: there is nothing dissimilar between the treated and control units, *except* for the application of treatment
        - Hence, if there is a difference in outcome between the two groups, it must be because of the treatment

The solution

To avoid this problem, we use **random assignment** of the treatment; we'll call this an **experiment**

- Units no longer self-select into treatment
- The researcher "decides" who gets the treatment
  - By "decide" we mean: randomly choose who gets treatment
- What does this do? Any ideas?
- It solves the selection bias
  - On average, treated and control units should be very similar
  - Intuitively: there is nothing dissimilar between the treated and control units, *except* for the application of treatment
    - Hence, if there is a difference in outcome between the two groups, it must be because of the treatment
  - In terms of POs: had the treated units not been treated, their outcome would be the same, on average, as the control units

Randomization and the FPCI

Have we solved the FPCI?

Randomization and the FPCI

Have we solved the FPCI?

- Well, we still can't observed both POs for any given unit

Randomization and the FPCI

Have we solved the FPCI?

- Well, we still can't observed both POs for any given unit
- But we've constructed a plausible **counterfactual**
- We are able to say:
  - I can't see $Y_i(0)$ for the treated units

Randomization and the FPCI

Have we solved the FPCI?

- Well, we still can't observed both POs for any given unit
- But we've constructed a plausible **counterfactual**
- We are able to say:
  - I can't see $Y_i(0)$ for the treated units
  - But if I can assume that it is the same as $Y_i(0)$ for the control units

Randomization and the FPCI

Have we solved the FPCI?

- Well, we still can't observed both POs for any given unit
- But we've constructed a plausible **counterfactual**
- We are able to say:
    - I can't see $Y_i(0)$ for the treated units
    - But if I can assume that it is the same as $Y_i(0)$ for the control units
    - Which we do observe!

Randomization example

Gerber, Green and Larimer (2008) are interested in the motivation to vote

- A long tradition in political science considers voting as individually irrational
- What's the benefit of voting?
- What's the cost of voting?

Pr(Voting) = P*B - C + D

Randomization example

Context: 2006 primary elections in Michigan

- In the US, voting records are public
- Mailers to about 180,000 households
- 5 conditions:
  - Control: $Y_i(0)$
  - "Civic Duty": $Y_i(CivicDuty)$
  - "Hawthorne": $Y_i(Hawthorne)$
  - "Self": $Y_i(Self)$
  - "Neighbors": $Y_i(Neighbors)$
- Outcome Y_i: whether subject voted (1/0)

Randomization example: Civic duty condition

APPENDIX A: MAILINGS

Civic Duty mailing

30426-2 XXX

For more information: (517) 351-1975
email: etov@grebner.com
Practical Political Consulting
P. O. Box 6249
East Lansing, MI 48826

PRSRT STD
U.S. Postage
PAID
Lansing, MI
Permit # 444

ECRLOT **C002
THE JONES FAMILY
9999 WILLIAMS RD
FLINT MI 48507

Dear Registered Voter:

DO YOUR CIVIC DUTY AND VOTE!

Why do so many people fail to vote? We've been talking about this problem for years, but it only seems to get worse.

The whole point of democracy is that citizens are active participants in government; that we have a voice in government. Your voice starts with your vote. On August 8, remember your rights and responsibilities as a citizen. Remember to vote.

DO YOUR CIVIC DUTY — VOTE!

Randomization example: Neighbors condition

Neighbors mailing

3 0 4 2 3 - 3

For more information: (517) 351-1975
email: etov@grebner.com
Practical Political Consulting
P. O. Box 6249
East Lansing, MI 48826

PRSRT STD
U.S. Postage
PAID
Lansing, MI
Permit # 444

ECRLOT **C050
THE JACKSON FAMILY
9999 MAPLE DR
FLINT MI 48507

Dear Registered Voter:

WHAT IF YOUR NEIGHBORS KNEW WHETHER YOU VOTED?

Why do so many people fail to vote? We've been talking about the problem for years, but it only seems to get worse. This year, we're taking a new approach. We're sending this mailing to you and your neighbors to publicize who does and does not vote.

The chart shows the names of some of your neighbors, showing which have voted in the past. After the August 8 election, we intend to mail an updated chart. You and your neighbors will all know who voted and who did not.

DO YOUR CIVIC DUTY — VOTE!

MAPLE DR	Aug 04	Nov 04	Aug 06
9995 JOSEPH JAMES SMITH	Voted	Voted	______
9995 JENNIFER KAY SMITH		Voted	______
9997 RICHARD B JACKSON		Voted	______
9999 KATHY MARIE JACKSON		Voted	______

Randomization example: the data

```
voting <- read.csv("lectures/lecture_4.2/gerber.csv")
cols <- c("female", "yob", "voting", "hawthorne",
          "civicduty", "neighbors", "self", "control")
voting <- voting[,cols]
kable(head(voting))
```

female	yob	voting	hawthorne	civicduty	neighbors	self	control
0	1941	0	0	1	0	0	0
1	1947	0	0	1	0	0	0
1	1982	1	1	0	0	0	0
1	1950	1	1	0	0	0	0
0	1951	1	1	0	0	0	0
1	1959	1	0	0	0	0	1

Randomization example: the data

```r
dim(voting)
```

```
## [1] 344084      8
```

```r
table(voting$voting)
```

```
##
##      0      1
## 235388 108696
```

Randomization example: Turnout in the control

```
voting_control <- voting[voting$control==1,] # subsetting the data
mean(voting_control$voting) # mean of dummy = proportion
```

```
## [1] 0.2966383
```

Randomization example: Turnout in the control

```r
voting_control <- voting[voting$control==1,] # subsetting the data
mean(voting_control$voting) # mean of dummy = proportion
```

```
## [1] 0.2966383
```

What's your hunch as to the size of the treatment effect?

Randomization example: The results

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

Who wants to interpret this?

Randomization example: The results

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

Who wants to interpret this?

- "Direction": Positive or negative effect?

Randomization example: The results

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

Who wants to interpret this?

- "Direction": Positive or negative effect?
- "Magnitude": How large is the effect?
  - Domain expertise is important in contextualizing
  - Do you think this is a large effect?

Randomization example: The results

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

Who wants to interpret this?

- "Direction": Positive or negative effect?
- "Magnitude": How large is the effect?
  - Domain expertise is important in contextualizing
  - Do you think this is a large effect?
- Can be interpreted causally?

Randomization example: Causal effect?

TABLE 1. Relationship between Treatment Group Assignment and Covariates (Household-Level Data)

	Control	Civic Duty	Hawthorne	Self	Neighbors
	Mean	Mean	Mean	Mean	Mean
Household size	1.91	1.91	1.91	1.91	1.91
Nov 2002	.83	.84	.84	.84	.84
Nov 2000	.87	.87	.87	.86	.87
Aug 2004	.42	.42	.42	.42	.42
Aug 2002	.41	.41	.41	.41	.41
Aug 2000	.26	.27	.26	.26	.26
Female	.50	.50	.50	.50	.50
Age (in years)	51.98	51.85	51.87	51.91	52.01
N =	99,999	20,001	20,002	20,000	20,000

Note: Only registered voters who voted in November 2004 were selected for our sample. Although not included in the table, there were no significant differences between treatment group assignment and covariates measuring race and ethnicity.

Who wants to try to interpret this?

Randomization example: Causal effect?

TABLE 1. Relationship between Treatment Group Assignment and Covariates (Household-Level Data)

	Control	Civic Duty	Hawthorne	Self	Neighbors
	Mean	Mean	Mean	Mean	Mean
Household size	1.91	1.91	1.91	1.91	1.91
Nov 2002	.83	.84	.84	.84	.84
Nov 2000	.87	.87	.87	.86	.87
Aug 2004	.42	.42	.42	.42	.42
Aug 2002	.41	.41	.41	.41	.41
Aug 2000	.26	.27	.26	.26	.26
Female	.50	.50	.50	.50	.50
Age (in years)	51.98	51.85	51.87	51.91	52.01
N =	99,999	20,001	20,002	20,000	20,000

Note: Only registered voters who voted in November 2004 were selected for our sample. Although not included in the table, there were no significant differences between treatment group assignment and covariates measuring race and ethnicity.

Who wants to try to interpret this?

- Randomization "works" $\rightsquigarrow$ groups are the same
  - The same in terms of POs under control (can we confirm?)

Randomization example: Causal effect?

TABLE 1. Relationship between Treatment Group Assignment and Covariates (Household-Level Data)

	Control	Civic Duty	Hawthorne	Self	Neighbors
	Mean	Mean	Mean	Mean	Mean
Household size	1.91	1.91	1.91	1.91	1.91
Nov 2002	.83	.84	.84	.84	.84
Nov 2000	.87	.87	.87	.86	.87
Aug 2004	.42	.42	.42	.42	.42
Aug 2002	.41	.41	.41	.41	.41
Aug 2000	.26	.27	.26	.26	.26
Female	.50	.50	.50	.50	.50
Age (in years)	51.98	51.85	51.87	51.91	52.01
N =	99,999	20,001	20,002	20,000	20,000

Note: Only registered voters who voted in November 2004 were selected for our sample. Although not included in the table, there were no significant differences between treatment group assignment and covariates measuring race and ethnicity.

Who wants to try to interpret this?

- Randomization "works" $\rightsquigarrow$ groups are the same
    - The same in terms of POs under control (can we confirm?)
    - And the same in terms of **pre-treatment covariates**
        - Pre-treatment covariate: a variable that is not/cannot be affected by the treatment

Experimental vs observational

In **experimental research**...

- The researcher has control over the treatment assignment mechanism

Experimental vs observational

In **experimental research**...

- The researcher has control over the treatment assignment mechanism
- Specifically, units are randomly assigned to different experimental conditions

Experimental vs observational

In **experimental research**...

- The researcher has control over the treatment assignment mechanism
- Specifically, units are randomly assigned to different experimental conditions

In **observational research**...

- The researcher gathers data on the units without having influence on treatment assignment

Experimental vs observational

In **experimental research**...

- The researcher has control over the treatment assignment mechanism
- Specifically, units are randomly assigned to different experimental conditions

In **observational research**...

- The researcher gathers data on the units without having influence on treatment assignment
- Units self-select into different values of the treatment/IV
- More about this later

Internal and external validity

Experimental and observational approaches are often compared in terms of validity

- **Internal validity**: The more plausible the claim about causality, the higher the internal validity

Internal and external validity

Experimental and observational approaches are often compared in terms of validity

- **Internal validity**: The more plausible the claim about causality, the higher the internal validity
- **External validity**: The results of the study can be *generalized* to the real world or beyond the case at hand
  - Remember: *generality* is an important scientific principle

Internal and external validity

Experimental and observational approaches are often compared in terms of validity

- **Internal validity**: The more plausible the claim about causality, the higher the internal validity
- **External validity**: The results of the study can be *generalized* to the real world or beyond the case at hand
    - Remember: *generality* is an important scientific principle

Different types of experiments

- Lab experiment: The "classic" experiment. Units are brought to the "lab," a controlled environment where the study takes place
    - More common before the Internet!
    - Advantage? Disadvantages?

Different types of experiments

- Lab experiment: The "classic" experiment. Units are brought to the "lab," a controlled environment where the study takes place
  - More common before the Internet!
  - Advantage? Disadvantages?
- Field experiment: takes place "in-the-field"
  - "aim to reproduce the environment in which the phenomenon of interest naturally occurs" Gerber (2011, 116)

Different types of experiments

- Lab experiment: The "classic" experiment. Units are brought to the "lab," a controlled environment where the study takes place
  - More common before the Internet!
  - Advantage? Disadvantages?
- Field experiment: takes place "in-the-field"
  - "aim to reproduce the environment in which the phenomenon of interest naturally occurs" Gerber (2011, 116)
  - Peyton et al. (2019): community policing and perceived legitimacy of police
  - Wantchekon (2003): randomly assigns clientelist policy platforms
  - Advantages/disadvantages?

Different types of experiments

- Lab experiment: The "classic" experiment. Units are brought to the "lab," a controlled environment where the study takes place
  - More common before the Internet!
  - Advantage? Disadvantages?
- Field experiment: takes place "in-the-field"
  - "aim to reproduce the environment in which the phenomenon of interest naturally occurs" Gerber (2011, 116)
  - Peyton et al. (2019): community policing and perceived legitimacy of police
  - Wantchekon (2003): randomly assigns clientelist policy platforms
  - Advantages/disadvantages?
- Survey experiment: embedded in a survey
  - e.g. randomly assign "global warming" or "climate change"
  - Advantages/disadvantages?

Why not randomize everything?

If randomization is so powerful, why not randomize everything?

Why not randomize everything?

If randomization is so powerful, why not randomize everything?

- There are some things we just can't randomize!
  - Either for ethical reasons – e.g. smoking
  - Or for more fundamental reasons – did civil rights protests in the 1960s influence vote choice? (Wasow 2020)

Why not randomize everything?

If randomization is so powerful, why not randomize everything?

- There are some things we just can't randomize!
  - Either for ethical reasons – e.g. smoking
  - Or for more fundamental reasons – did civil rights protests in the 1960s influence vote choice? (Wasow 2020)
- Experiments sometimes have limited external validity
  - Iyengar et al.'s (1982) lab experiments on media effects

Still useful to think about the "experimental ideal"

- If I *could* conduct an experiment, what would it look like?

Why not randomize everything?

If randomization is so powerful, why not randomize everything?

- There are some things we just can't randomize!
  - Either for ethical reasons – e.g. smoking
  - Or for more fundamental reasons – did civil rights protests in the 1960s influence vote choice? (Wasow 2020)
- Experiments sometimes have limited external validity
  - Iyengar et al.'s (1982) lab experiments on media effects

Still useful to think about the "experimental ideal"

- If I *could* conduct an experiment, what would it look like?

And look for randomness inherent to the world

Butler and Broockman

- What sort of experiment do they conduct?
- Internal and external validity?
- What do they conclude, and how convincing is it?
- Any drawbacks to their design?

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

- Except it's not really an experiment!
    - The researcher does not have control over the treatment assignment mechanism

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

- Except it's not really an experiment!
  - The researcher does not have control over the treatment assignment mechanism
- Instead, we'll say the treatment is **as-if random**

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

- Except it's not really an experiment!
  - The researcher does not have control over the treatment assignment mechanism
- Instead, we'll say the treatment is **as-if random**
- No one randomized the treatment
- Instead, "nature" took care of that for us

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

- Except it's not really an experiment!
  - The researcher does not have control over the treatment assignment mechanism
- Instead, we'll say the treatment is **as-if random**
- No one randomized the treatment
- Instead, "nature" took care of that for us

Examples of randomness we could exploit?

The search for quasi-experiments

Our last type of experiment: quasi-experiments/natural experiments

- Except it's not really an experiment!
  - The researcher does not have control over the treatment assignment mechanism
- Instead, we'll say the treatment is **as-if random**
- No one randomized the treatment
- Instead, "nature" took care of that for us

Examples of randomness we could exploit?

Some examples of randomness we can exploit

- What is the effect of judge's personal circumstances on their decisions?
  - Having a daughter: causes more feminist decisions by US judges (Glynn and Sen 2015)

Some examples of randomness we can exploit

- What is the effect of judge's personal circumstances on their decisions?
  - Having a daughter: causes more feminist decisions by US judges (Glynn and Sen 2015)
- What is the effect of socio-economic status on attitudes toward redistribution?
  - Lottery winners and attitudes toward redistribution (Doherty, Gerber, and Green 2006)

Some examples of randomness we can exploit

- What is the effect of judge's personal circumstances on their decisions?
  - Having a daughter: causes more feminist decisions by US judges (Glynn and Sen 2015)
- What is the effect of socio-economic status on attitudes toward redistribution?
  - Lottery winners and attitudes toward redistribution (Doherty, Gerber, and Green 2006)
- What is the effect of enrolling in the army on political attitudes?
  - The Vietnam draft lottery (Erikson and Stoker 2011)

Some examples of randomness we can exploit

- What is the effect of judge's personal circumstances on their decisions?
  - Having a daughter: causes more feminist decisions by US judges (Glynn and Sen 2015)
- What is the effect of socio-economic status on attitudes toward redistribution?
  - Lottery winners and attitudes toward redistribution (Doherty, Gerber, and Green 2006)
- What is the effect of enrolling in the army on political attitudes?
  - The Vietnam draft lottery (Erikson and Stoker 2011)
- Do autocratic regimes depend on their leaders?
  - The success or failure of assassination attempts and future democratization (Jones and Olken 2009)

Some examples of randomness we can exploit

- What is the effect of judge's personal circumstances on their decisions?
    - Having a daughter: causes more feminist decisions by US judges (Glynn and Sen 2015)
- What is the effect of socio-economic status on attitudes toward redistribution?
    - Lottery winners and attitudes toward redistribution (Doherty, Gerber, and Green 2006)
- What is the effect of enrolling in the army on political attitudes?
    - The Vietnam draft lottery (Erikson and Stoker 2011)
- Do autocratic regimes depend on their leaders?
    - The success or failure of assassination attempts and future democratization (Jones and Olken 2009)

Observational research

We frequently can't randomize or find a quasi-experiment

- So we are left with observational data
- Observational data is not useless – far from it!
- But it can be harder to establish causality

The typical problem: spurious relationships

- An observed relationship between x and y, but not a *causal* one
- Why? The relationship is **confounded** by some variable z
    - Z *confounds* the relationship between x and y if it is correlated with both
- These spurious relationships show up a lot in observational research
    - They can trick you into thinking there's a causal effect – even when there's not!

Examples of spuriousness

- Correlation between sleeping with shoes and waking up with a headache
    - What's a potential confounder here?

Examples of spuriousness

- Correlation between sleeping with shoes and waking up with a headache
  - What's a potential confounder here?
  - Being drunk!

Examples of spuriousness

- Correlation between sleeping with shoes and waking up with a headache
  - What's a potential confounder here?
  - Being drunk!
- Any other examples?

Examples of spuriousness

- Correlation between sleeping with shoes and waking up with a headache
  - What's a potential confounder here?
  - Being drunk!
- Any other examples?

The total observed association between X and Y is: a mixture of causal and confounding association

- Once I "control" for z, there may be no relationship between X and Y
- Once I "control" for z, the relationship between X and Y may be weaker
- Once I "control" for z, the relationship between X and Y may change direction

Many sources of spuriousness

The problem with observational research is that there may be many such z variables!

- i.e. many variables may confound the relationship between x and y
- In which case, to recover the true causal effect, I would need to "control for" all of these confounders

Many sources of spuriousness

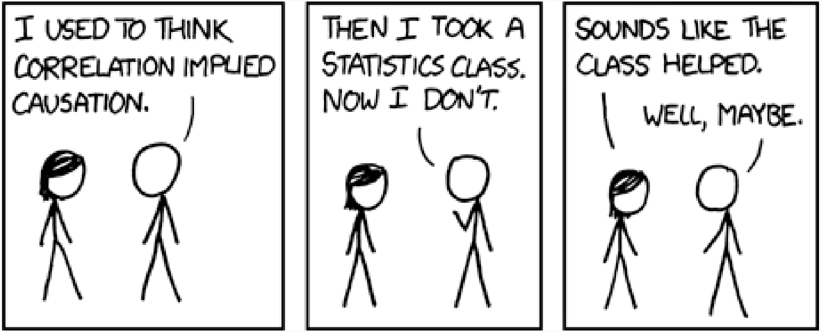
The problem with observational research is that there may be many such z variables!

- i.e. many variables may confound the relationship between x and y
- In which case, to recover the true causal effect, I would need to "control for" all of these confounders

Let's think of the example: office hours -> grade in the class

- What are some potential confounders here?

Is this class causing better outcomes?



Concluding our section on causality

Main takeaways:

- The FPCI makes things difficult; adjust confidence accordingly!
- A lot of observed correlations are non-causal
- Randomization “solves” the selection problem and makes inferring causality much easier
- But not always possible! So look for randomness inherent to the world

References i

Doherty, Daniel, Alan S. Gerber, and Donald P. Green. 2006. "Personal Income and Attitudes Toward Redistribution: A Study of Lottery Winners." *Political Psychology* 27 (3): 441–58. https://doi.org/10.1111/j.1467-9221.2006.00509.x.

Erikson, Robert S., and Laura Stoker. 2011. "Caught in the Draft: The Effects of Vietnam Draft Lottery Status on Political Attitudes." *American Political Science Review* 105 (2): 221–37. https://doi.org/10.1017/S0003055411000141.

Gerber, Alan S. 2011. "Field Experiments in Political Science." In *Cambridge Handbook of Experimental Political Science*, edited by Arthur Lupia, Donald P. Greene, James H. Kuklinski, and James N. Druckman, 115–38. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511921452.009.

References ii

Gerber, Alan S., Donald P. Green, and Christopher W. Larimer. 2008. "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment." *American Political Science Review* 102 (1): 33–48. https://doi.org/10.1017/S000305540808009X.

Glynn, Adam N., and Maya Sen. 2015. "Identifying Judicial Empathy: Does Having Daughters Cause Judges to Rule for Women's Issues?" *American Journal of Political Science* 59 (1): 37–54. https://doi.org/https://doi.org/10.1111/ajps.12118.

Iyengar, Shanto, Mark D. Peters, and Donald R. Kinder. 1982. "Experimental Demonstrations of the 'Not-So-Minimal' Consequences of Television News Programs." *American Political Science Review* 76 (4): 848–58. https://doi.org/10.1017/S000305540018966X.

Jones, Benjamin F., and Benjamin A. Olken. 2009. "Hit or Miss? The Effect of Assassinations on Institutions and War." *American Economic Journal: Macroeconomics* 1 (2): 55–87. https://doi.org/10.1257/mac.1.2.55.

Peyton, Kyle, Michael Sierra-Arévalo, and David G. Rand. 2019. "A Field Experiment on Community Policing and Police Legitimacy." *Proceedings of the National Academy of Sciences* 116 (40): 19894–98. https://doi.org/10.1073/pnas.1910157116.

Wantchekon, Leonard. 2003. "Clientelism and Voting Behavior: Evidence from a Field Experiment in Benin." *World Politics* 55 (3): 399–422. https://doi.org/10.1353/wp.2003.0018.

Wasow, Omar. 2020. "Agenda Seeding: How 1960s Black Protests Moved Elites, Public Opinion and Voting." *American Political Science Review* 114 (3): 638–59. https://doi.org/10.1017/S000305542000009X.