Survey Experiments

POLSCI 4SS3

Winter 2024

Last week

- We discussed and explored techniques to reduce sensitivity bias
- Some techniques are **observational** `(e.g. randomized response)`
- Some techniques are **experimental** `(e.g. list experiment)`
- **Today:** Discuss surveys using experiments more generally

Survey experiments

Return to parallels

Theory	Empirics
Model	Data strategy
Inquiry	Answer strategy

Return to parallels

Theory	**Empirics**
Model	Data strategy
Inquiry	**Answer strategy**

Types of survey research design

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive		
Causal		

Types of survey research design

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	
Causal		

Types of survey research design

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	List experiment
Causal		

Types of survey research design

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	List experiment
Causal	Panel survey	

Types of survey research design

	Data strategy	
Inquiry	**Observational**	**Experimental**
Descriptive	Sample survey	List experiment
Causal	Panel survey	Survey experiment

Survey experiments are **experimental** data strategies that answer a **causal** inquiry

Survey experiments

- Assign respondents to **conditions** or **treatments**
- Usually by **random assignment**
- Each condition is a different version of a **question** or **vignette**
- **Goal:** Understand the effect of different conditions on the outcome question if interest
- How does this work?

Taking a step back

- Two ways to express functional relations in a **model**

1. Structural causal models
2. Potential outcomes framework

Taking a step back

- Two ways to express functional relations in a **model**

1. Structural causal models
2. **Potential outcomes framework**

Potential outcomes framework

Notation

- i: unit of analysis `(e.g. individuals, schools, countries)`
- $Z_i = \{0, 1\}$ indicates a condition `(1: Treatment, 0: Control)`
- $Y_i(Z_i)$ is the individual **potential outcome**
- $Y_i(0)$: Potential outcome under control
- $Y_i(1)$: Potential outcome under treatment

Toy example

ID	Female	$Y_i(1)$	$Y_i(0)$
1	0	0	0
2	0	1	0
3	1	1	0
4	1	1	1

- $\tau_i = Y_i(1) - Y_i(0)$ is the **individual causal effect**

Toy example

ID	Female	$Y_i(1)$	$Y_i(0)$	τ_i
1	0	0	0	0
2	0	1	0	1
3	1	1	0	1
4	1	1	1	0

- $\tau_i = Y_i(1) - Y_i(0)$ is the **individual causal effect**
- $\tau = (1/n)\sum_{i=1}^{n} \tau_i = E[\tau_i]$ is the **inquiry** or **estimand**
- We call τ the **Average Treatment Effect (ATE)**

Notation chart

Greek

- Letters like μ denote **estimands**
- A hat $\hat{\mu}$ denotes **estimators**

Latin

- Letters like X denote **actual variables** in our data
- A bar $\bar{X}$ denotes an **estimate** calculated from our data

$$X \rightarrow \bar{X} \rightarrow \hat{\mu} \xrightarrow{\text{hopefully!}} \mu$$

$$\text{Data} \rightarrow \text{Estimate} \rightarrow \text{Estimator} \xrightarrow{\text{hopefully!}} \text{Estimand}$$

Challenge

- We want to know the ATE τ
- This requires us to know $\tau_i = Y_i(1) - Y_i(0)$
- But when we assign treatment conditions we only observe one of the potential outcomes $Y_i(1)$ or $Y_i(0)$
- Meaning that τ_i is impossible to calculate!
- This is the **fundamental problem of causal inference**

Continuing the example

		Unobserved		
ID	**Female**	$Y_i(1)$	$Y_i(0)$	τ_i
1	0	0	0	0
2	0	1	0	1
3	1	1	0	1
4	1	1	1	0

- We can randomly assign conditions Z_i

Continuing the example

		Unobserved			Observed	
ID	Female	$Y_i(1)$	$Y_i(0)$	τ_i	Z_i	Y_i
1	0	0	0	0	1	0
2	0	1	0	1	0	0
3	1	1	0	1	1	1
4	1	1	1	0	0	1

- We observe outcome Y_i depending on assigned condition Z_i
- We can use this to approximate the ATE with an **estimator**

Estimator for the ATE

- **Additive property of expectations:**

$$
\begin{aligned}
\tau = E[\tau_i] &= E[Y_i(1) - Y_i(0)] \\
= &\underbrace{E[Y_i(1)] - E[Y_i(0)]}_{\text{Difference in means between potential outcomes}}
\end{aligned}
$$

- We cannot calculate this, but we can calculate

$$
\hat{\tau} = \underbrace{E[Y_i(1)|Z_i = 1] - E[Y_i(0)|Z_i = 0]}_{\text{Difference in means between conditions}}
$$

Randomization

- If we can claim that units are selected into conditions Z_i independently from potential outcomes
- Then we can claim that $\hat{\tau}$ is a *valid* approximation of τ
- In which case we say that $\hat{\tau}$ is an **unbiased** estimator of the ATE
- Random assignment of units into conditions guarantees this *in expectation*

Discussion

Tomz and Weeks (2013): "Public Opinion and the Democratic Peace"

- Surveys in the UK ($n = 762$) and US ($n = 1273$)
- April-May 2010
- **Outcome:** Support for military strike
- 2x2x2 survey experiment

Vignette design

UK

- **Political regime:** Democracy/not a democracy
- **Military alliances:** Ally/not an ally
- **Military power:** As strong/half as strong

US

- **Political regime:** Democracy/not a democracy
- **Military alliances:** Ally/not an ally
- **Trade:** High level/not high level

Results for democracy

TABLE 1. The Effect of Democracy on Willingness to Strike

	United Kingdom (between)	United States (between)	United States (within)
Not a democracy	34.2	53.3	50.0
Democracy	20.9	41.9	38.5
Effect of democracy	−13.3	−11.4	−11.5
95% C.I.	(−19.6 to −6.9)	(−17.0 to −5.9)	(−14.7 to −8.3)

Results for other factors

TABLE 2. The Effect of Alliances, Power, and Trade

	United Kingdom	United States
No military alliance	30.7	50.2
Military alliance	25.1	45.1
Effect of alliance	−5.7	−5.1
95% C.I.	(−12.0 to 0.6)	(−10.7 to 0.5)
Half as strong	29.3	
As strong	26.3	
Effect of strength	−3.0	
95% C.I.	(−9.4 to 3.2)	
No high trade		50.3
High trade		45.1
Effect of high trade		−5.2
95% C.I.		(−10.6 to 0.2)

Eggers et al (2017): “Corruption, Accountability, and Gender”

Constituency A

This is a marginal constituency won narrowly by **the Conservatives** at the last election. Based on polls, the **only other party with a chance of winning** this seat are **Labour**. Here are the details of the current **Conservative** MP and the **Labour** challenger:

Current MP:	Main challenger:
Conservative	Labour
64 years old	62 years old
Female	Female
Formerly a business manager	Formerly a business manager

Last year, the current MP was found to have **inappropriately claimed over £10,000** on expenses.

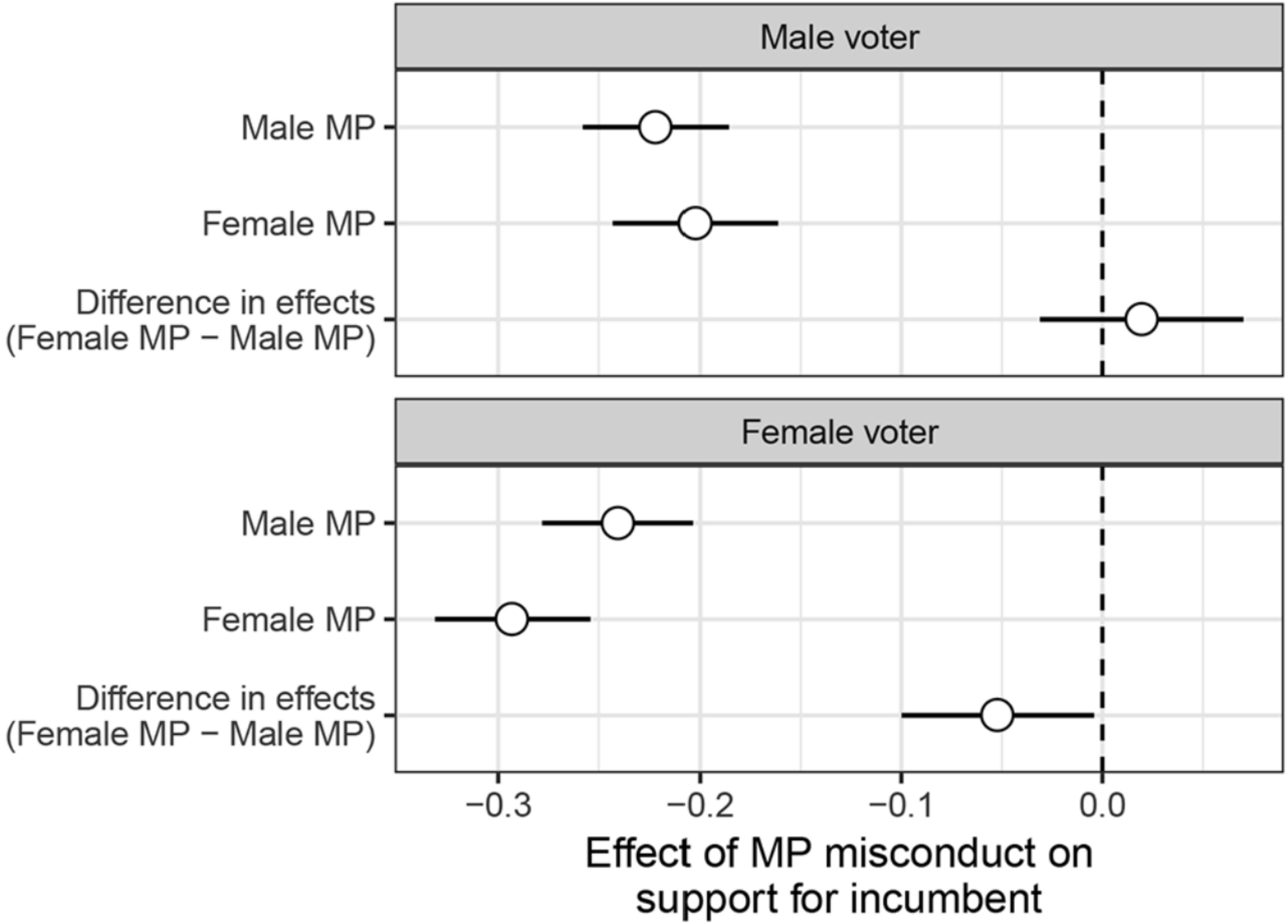
If you were living in this constituency at the next general election, who would you vote for?

- ◯ The current Conservative MP
- ◯ The Labour challenger
- ◯ The Liberal Democrat candidate
- ◯ A candidate from another party
- ◯ No one, I would not vote

Profile variants

Factor	MP	Challenger
Party	Labour, Conservative	Labour, Conservative, Liberal Democrat
Age	45, 52, 64	40, 52, 64
Gender	Male, Female	Male, Female
Previous job	General practitioner, journalist, political advisor, teacher, business manager	General practitioner, journalist, political advisor, teacher, business manager

Results



Male voter
Male MP
Female MP
Difference in effects
(Female MP − Male MP)
Female voter
Male MP
Female MP
Difference in effects
(Female MP − Male MP)
−0.3
−0.2
−0.1
0.0
Effect of MP misconduct on
support for incumbent

Next Week

Convenience Samples

Focus on: Should findings generalize?

Break time!

Lab