# Survey Experiments

POLSCI 4SS3

Winter 2023

# Announcements

- Schedule group meetings before break!
- Need help with R? Check the Data Analysis Support Hub at Mac
- You can book virtual research consultations with an expert

# 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

# Types of survey research design

| | Data strategy | |
|---|---|---|
| Inquiry | Observational | Experimental |
| Descriptive | | |
| Causal | | |

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| **Descriptive** | Sample survey | List experiment |
| **Causal** | Panel survey | Survey experiment |

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

Technically, list experiments are survey experiments too.

# Survey experiments

- Assign respondents to **conditions**
- 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

1. **Structural causal models** `(two weeks ago)`
2. **Potential outcomes framework** `(today)`

# 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 | $Y_i(1)$ | $Y_i(0)$ | $\tau_i$ |
|---|---|---|---|---|
| 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**
- We call $\tau$ the **Average Treatment Effect (ATE)**

# A note on notation

## Greek

- Letters like $\mu$ 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

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

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

# Challenge

- We want to know the ATE $\tau$
- 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 $\tau_i$ is impossible to calculate!
- This is the **fundamental problem of causal inference**

# Continuing the example

| | | Unobserved | | |
|---|---|---|---|---|
| ID | Female | $Y_i(1)$ | $Y_i(0)$ | $\tau_i$ |
| 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 | $Y_i(1)$ | $Y_i(0)$ | $\tau_i$ | $Z_i$ | $Y_i$ |
| 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 good approximation of $\tau$
- 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*

# Assumptions

**1. Ignorability**

Assignment to conditions does not depend on potential outcomes. This is guaranteed if randomization works properly.

**2. Non-interference**

Individual potential outcomes do not depend on the treatment assignment of others. If they do, then we need a more complicated model.

- We cannot evaluate these assumptions with data but we can convince our audience with careful research design

# 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”

<u>Constituency A</u>

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<br>64 years old<br>Female<br>Formerly a business manager | Labour<br>62 years old<br>Female<br>Formerly a business manager |

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

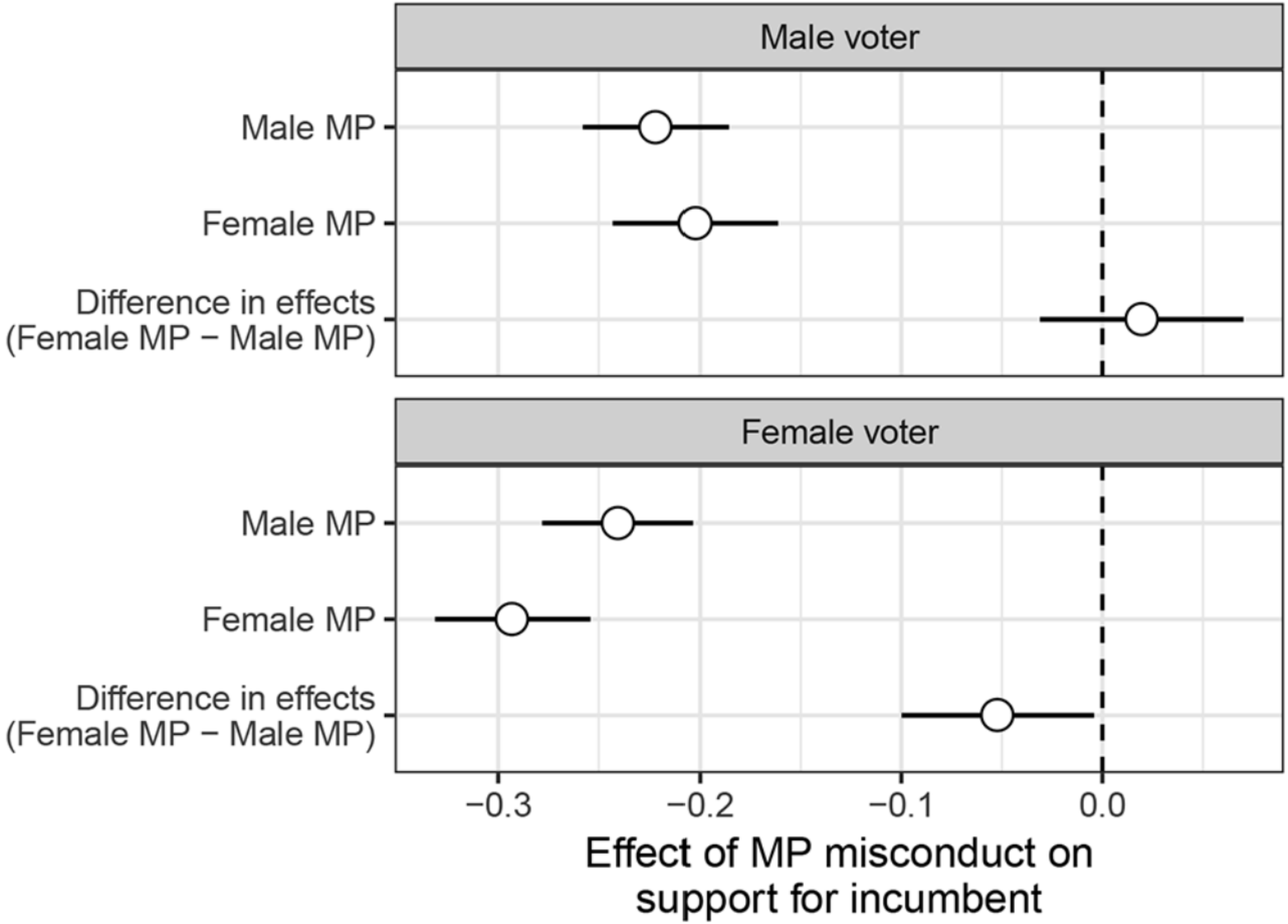
**If you were living in this constituency at the next general election, who would you vote for?**

- ◯ 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