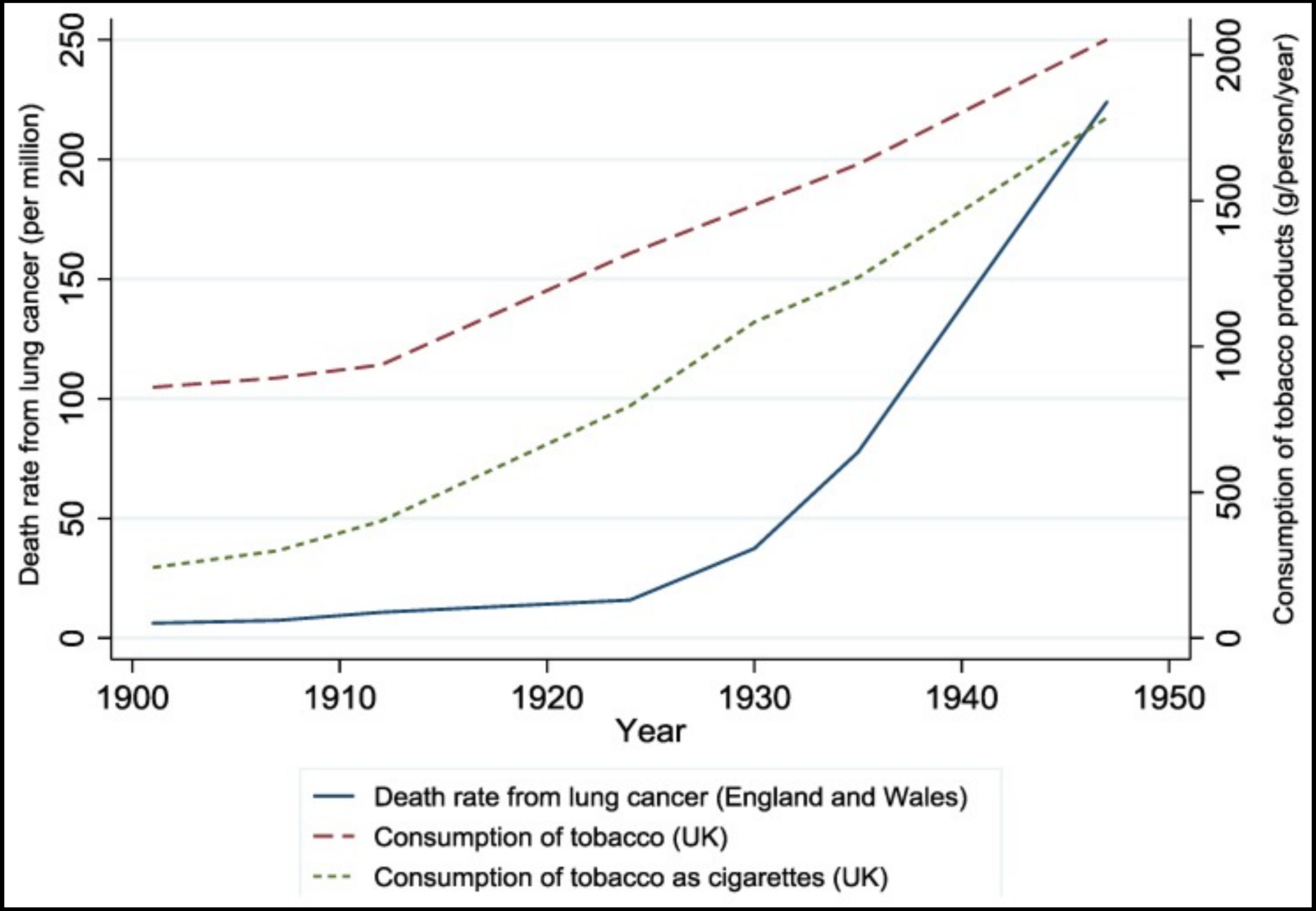
Experimental Methodology

Libby Jenke
Assistant Professor, University of Houston
July 26, 2021

- What is the effect of intermittent fasting on health? Lifespans? Alzheimers? Cancer?
- Are people’s party identifications motivated by their issue positions, or do they choose issue positions according to their parties?
- Does a person’s taste in music cause his/her personality traits?
- Does Facebook cause people to get addicted to it?



From Lucas and Harris, 2018

Cellular Pathology

- 1956 Hilding confirmed pulmonary ciliostasis among smokers where cancers likely to develop
- Auerbach’s 1957 autopsy studies showed precancerous changes in the cells of smokers

Distinguished authorities point out:

1. **That medical research of recent years indicates many possible causes of lung cancer.**
2. **That there is no agreement among the authorities regarding what the cause is.**
3. **That there is no proof that cigarette smoking is one of its causes.**
4. **That statistics purporting to link cigarette smoking with the disease could apply with equal force to any one of many aspects of modern life. Indeed the validity of the statistics themselves is questioned by numerous scientists.**

A Frank Statement to Cigarette Smokers

RECENT REPORTS on experiments with mice have given wide publicity to a theory that cigarette smoking is in some way linked with lung cancer in human beings.

Although conducted by doctors of professional standing, these experiments are not regarded as conclusive in the field of cancer research. However, we do not believe that any serious medical research, even though its results are inconclusive should be disregarded or lightly dismissed.

At the same time, we feel it is in the public interest to call attention to the fact that eminent doctors and research scientists have publicly questioned the claimed significance of these experiments.

Distinguished authorities point out:

1. That medical research of recent years indicates many possible causes of lung cancer.

2. That there is no agreement among the authorities regarding what the cause is.

3. That there is no proof that cigarette smoking is one of the causes.

4. That statistics purporting to link cigarette smoking with the disease could apply with equal force to any one of many other aspects of modern life. Indeed the validity of the statistics themselves is questioned by numerous scientists.

We accept an interest in people's health as a basic responsibility, paramount to every other consideration in our business.

We believe the products we make are not injurious to health.

We always have and always will cooperate closely with those whose task it is to safeguard the public health.

For more than 300 years tobacco has given solace, relaxation, and enjoyment to mankind. At one time or another during those years critics have held it responsible for practically every disease of the human body. One by one these charges have been abandoned for lack of evidence.

Regardless of the record of the past, the fact that cigarette smoking today should even be suspected as a cause of a serious disease is a matter of deep concern to us.

Many people have asked us what we are doing to meet the public's concern aroused by the recent reports. Here is the answer:

1. **We are pledging aid and assistance to the research effort into all phases of tobacco use and health. This joint financial aid will of course be in addition to what is already being contributed by individual companies.**
2. **For this purpose we are establishing a joint industry group consisting initially of the undersigned. This group will be known as TOBACCO INDUSTRY RESEARCH COMMITTEE.**
3. **In charge of the research activities of the Committee will be a scientist of unimpeachable integrity and national repute. In addition there will be an Advisory Board of scientists disinterested in the cigarette industry. A group of distinguished men from medicine, science, and education will be invited to serve on this Board. These scientists will advise the Committee on its research activities.**

This statement is being issued because we believe the people are entitled to know where we stand on this matter and what we intend to do about it.

TOBACCO INDUSTRY RESEARCH COMMITTEE

5400 EMPIRE STATE BUILDING, NEW YORK 1, N. Y.

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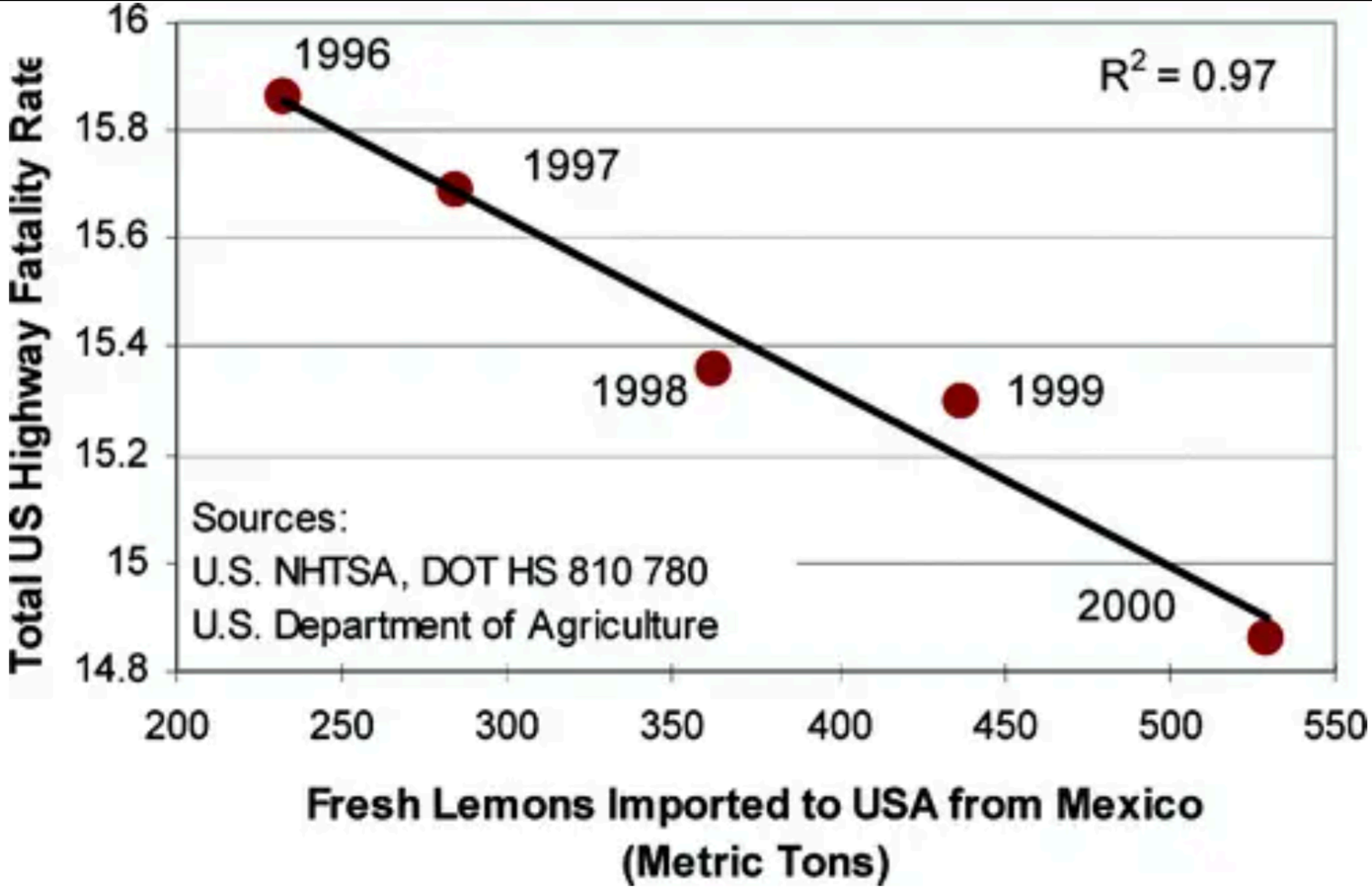
“The causal significance of association is a matter of judgment”

1966 survey: 60% smokers agreed that cancer link was not proved because it was “only based on statistics”



Total US Highway Fatality Rate
16
15.8
15.6
15.4
15.2
15
14.8
1996
1997
1998
1999
2000
$R^2 = 0.97$
Sources:
U.S. NHTSA, DOT HS 810 780
U.S. Department of Agriculture
200
250
300
350
400
450
500
550
Fresh Lemons Imported to USA from Mexico
(Metric Tons)

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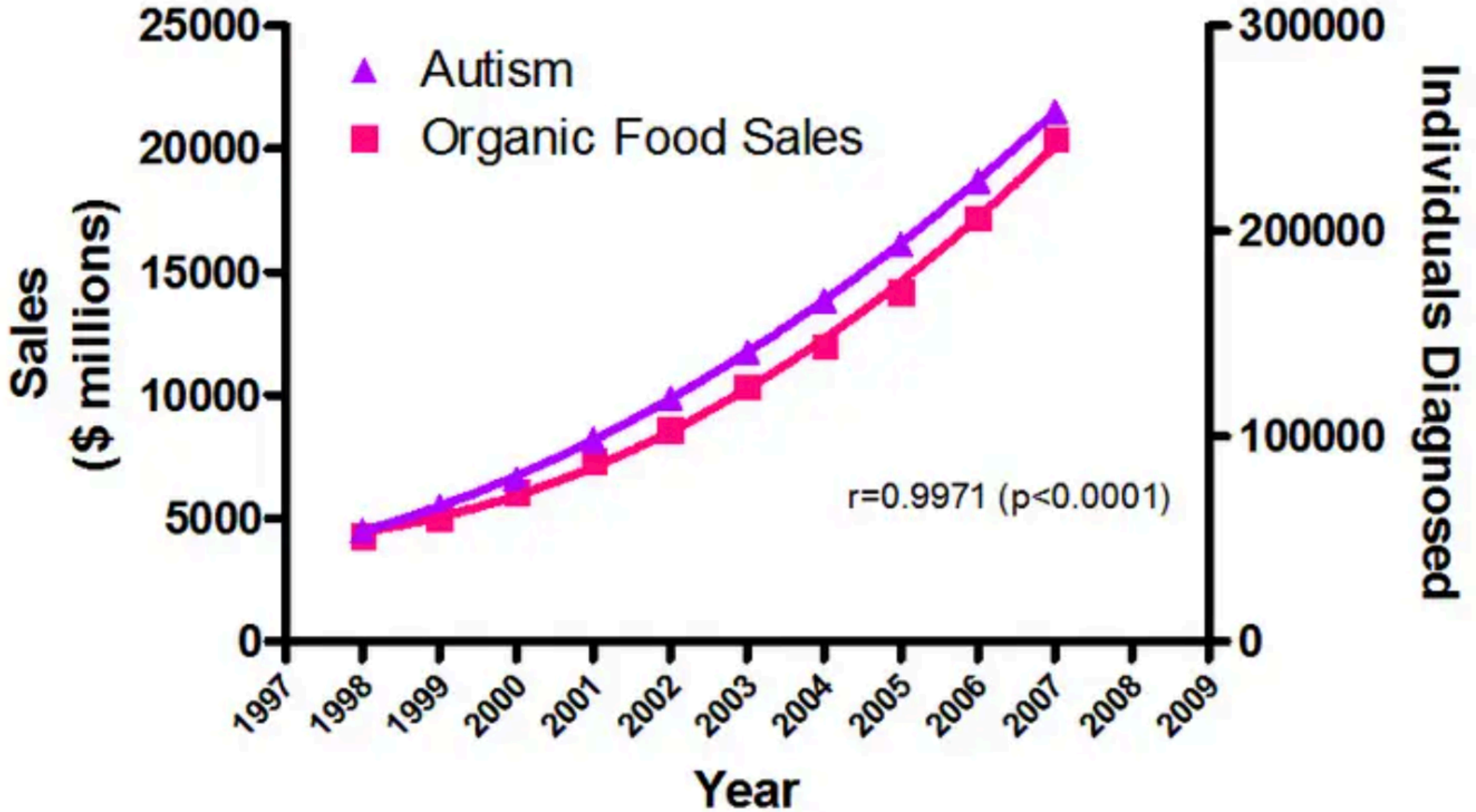
The real cause of increasing autism prevalence?



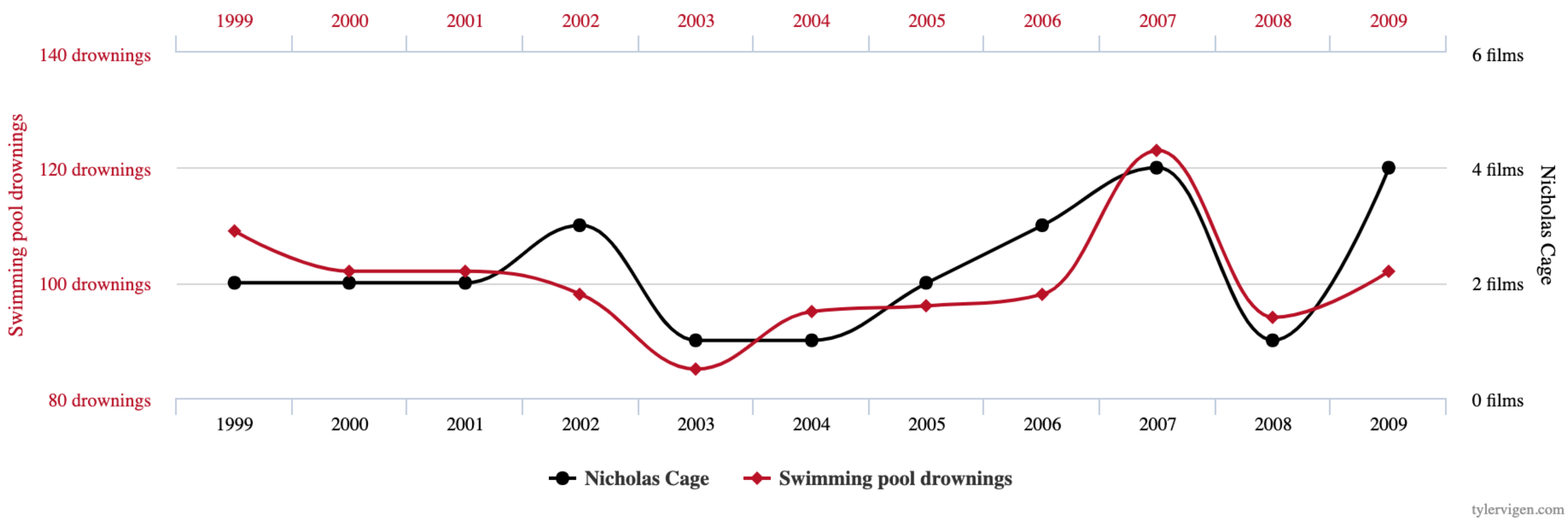
Sources: Organic Trade Association, 2011 Organic Industry Survey; U.S. Department of Education, Office of Special Education Programs, Data Analysis System (DANS), OMB# 1820-0043: "Children with Disabilities Receiving Special Education Under Part B of the Individuals with Disabilities Education Act

Number of people who drowned by falling into a pool

correlates with

Films Nicolas Cage appeared in

Correlation: 66.6% (r=0.666004)



Data sources: Centers for Disease Control & Prevention and Internet Movie Database

1. Why do experiments work? (Potential outcomes model)
2. Experimental design and implementation
   - Within vs. between subject designs
   - Internal vs. external validity
     - Convenience samples
     - Confounders and randomization checks
   - Blocking
   - Breakout rooms: experimental designs
3. Conjoint experiments
   - Theory
   - Implementation: code

What is an experiment?

Randomized: treatment and control units assigned by chance

Randomized experiments (lab, real world, or online), quasi-experiment (RD)/natural experiments

Why do a randomized experiment?

Allow better identification of causal effects

When to do an experiment?

Unclear causality: e.g., partisanship and policy positions / Facebook and addiction

Lots of potential covariates: e.g., athletic performance and sleep

But, see Ratkovic and Tingley (forthcoming)

IV can be manipulated: e.g., a voter's sex vs. a voter's attention to political news

- What is the effect of intermittent fasting on health? Lifespans? Alzheimers? Cancer?
- Are people's party identifications motivated by their issue positions, or do they choose issue positions according to their parties?
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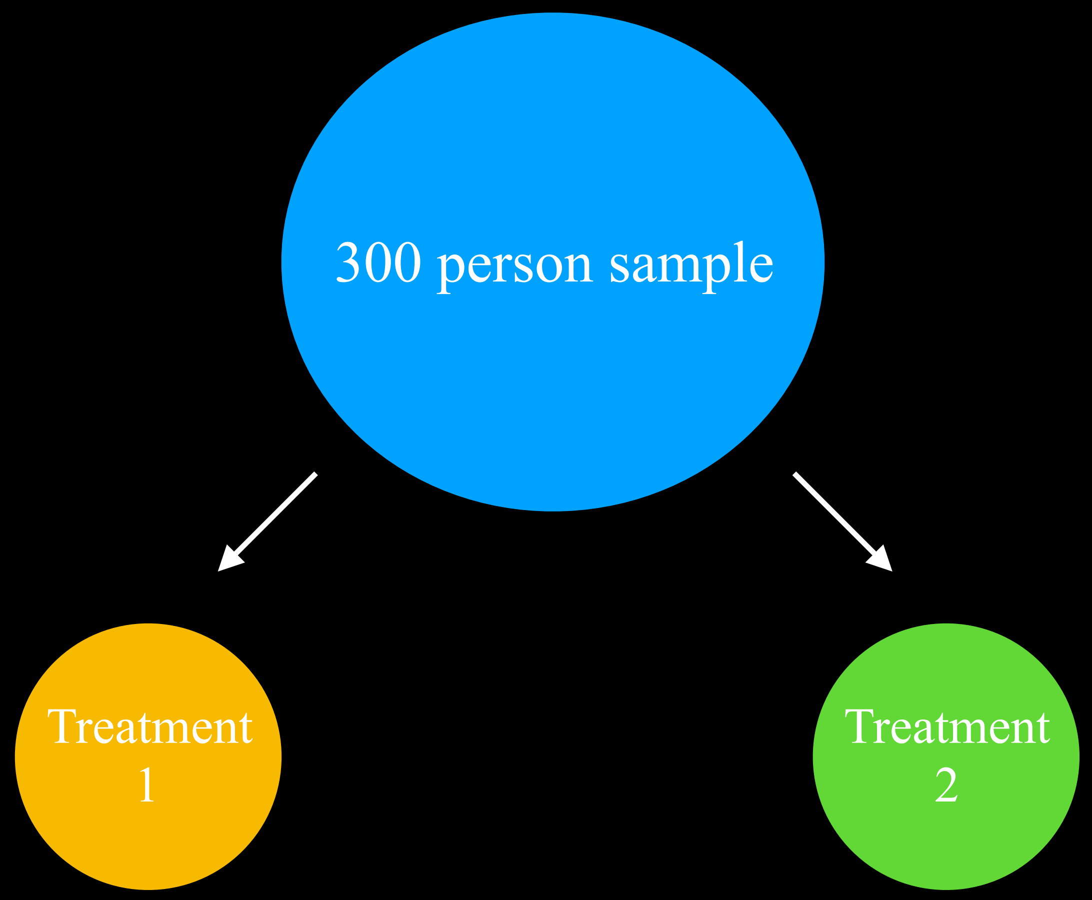
- Does Facebook cause people to get addicted to it?

Potential Outcomes Model

Why Does Randomization Work?



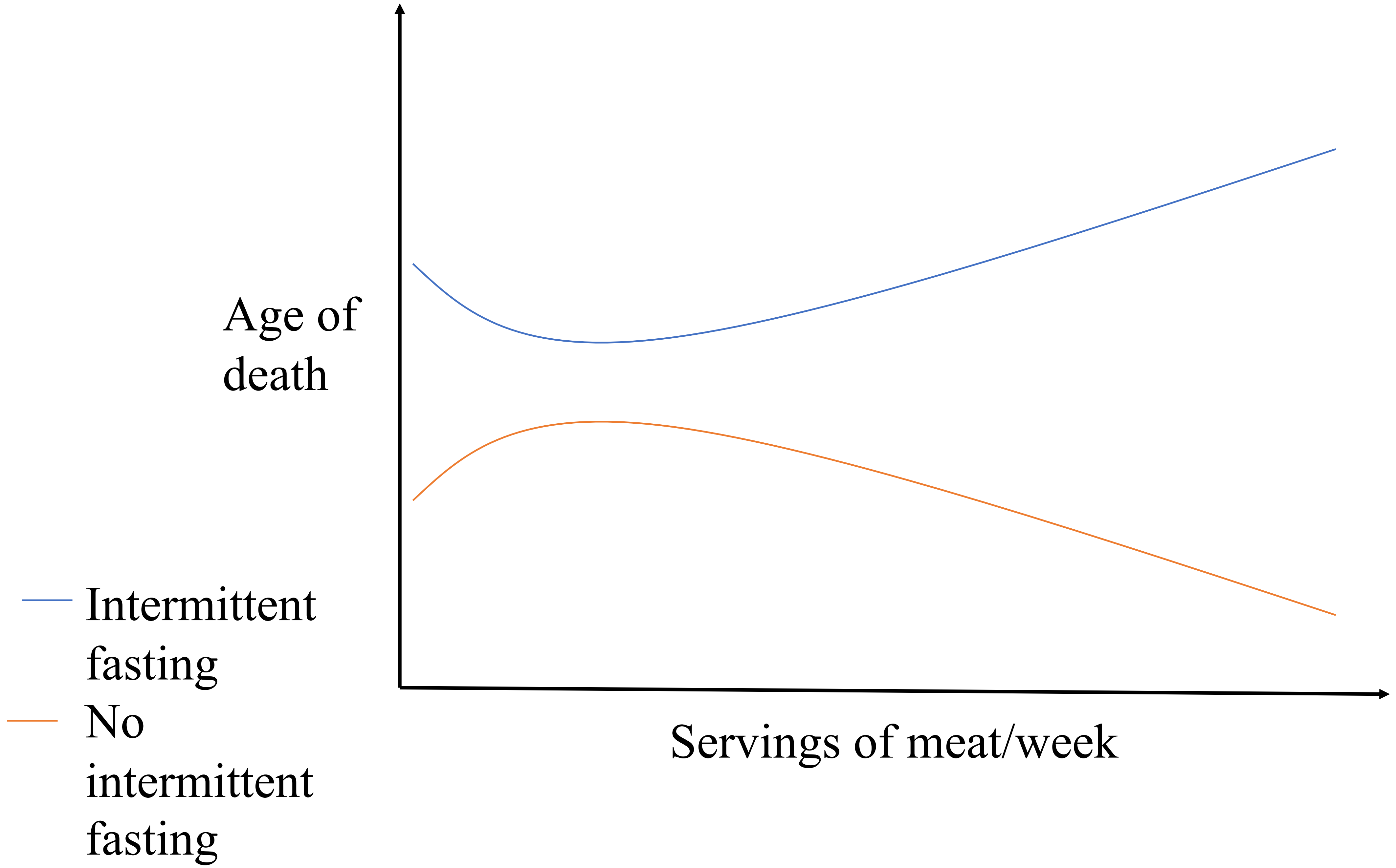
H1: People rate female candidates lower on likability scales because they are female

Treatment 1: male candidate

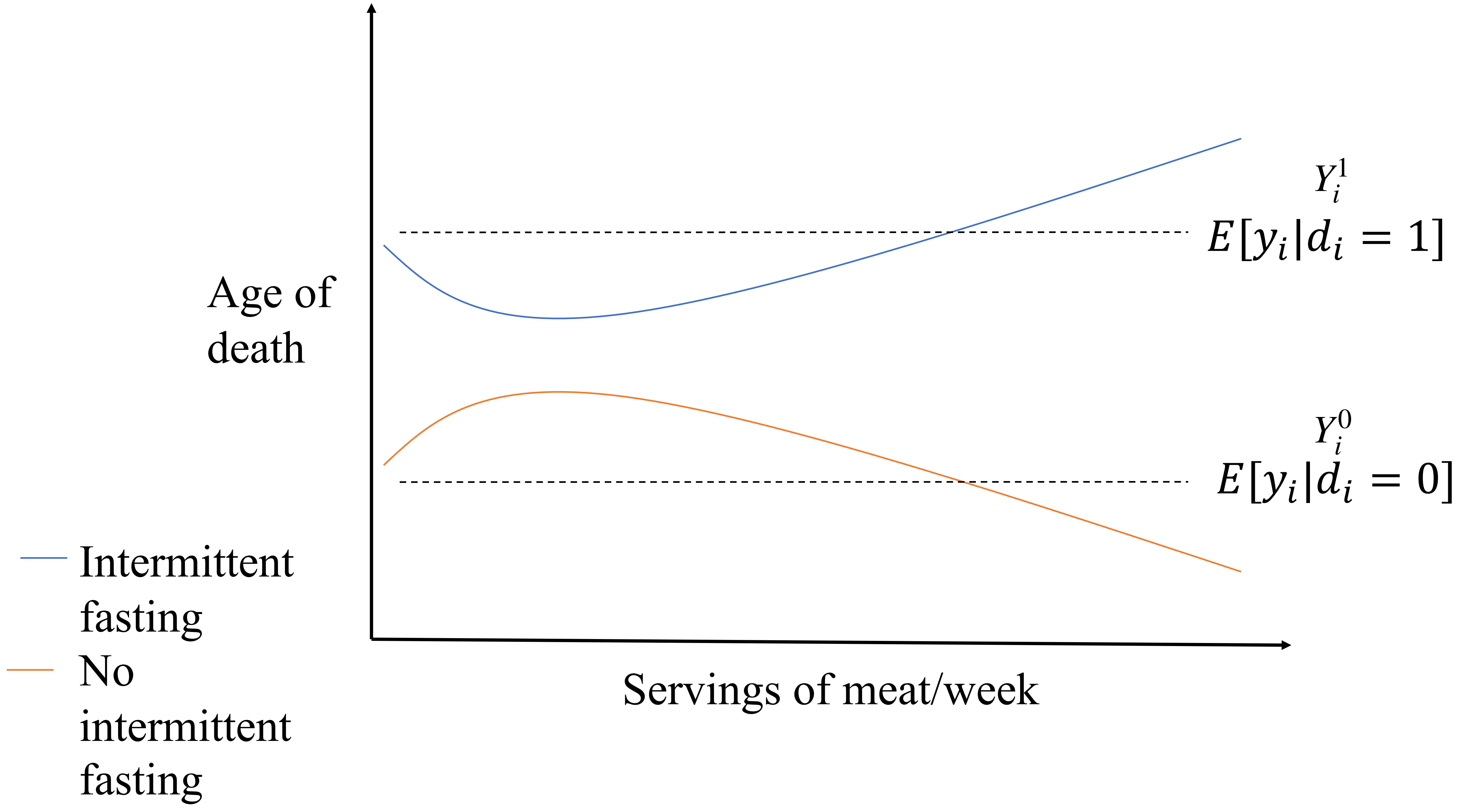
Treatment 2: female candidate

Causal Inference: Potential Outcomes

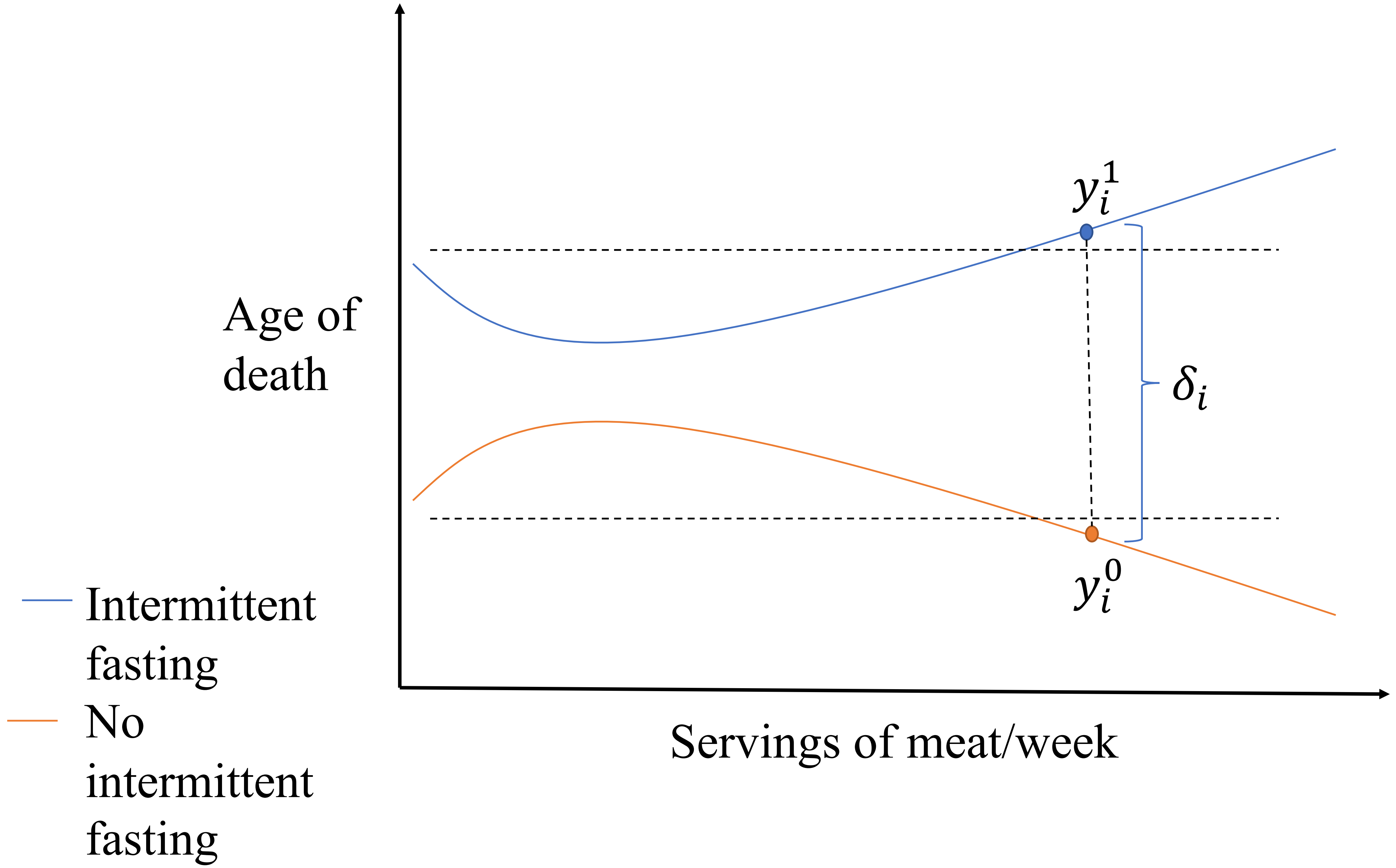
- Each unit i exposed to a binary treatment
- Potential outcomes: Y_i^1, Y_i^0
- Individ-level causal effect of treatment: $\delta_i = y_i^1 - y_i^0$
- Treatment: $D_i = 1$; Control: $D_i = 0$



Age of death
Servings of meat/week
Intermittent fasting
No intermittent fasting

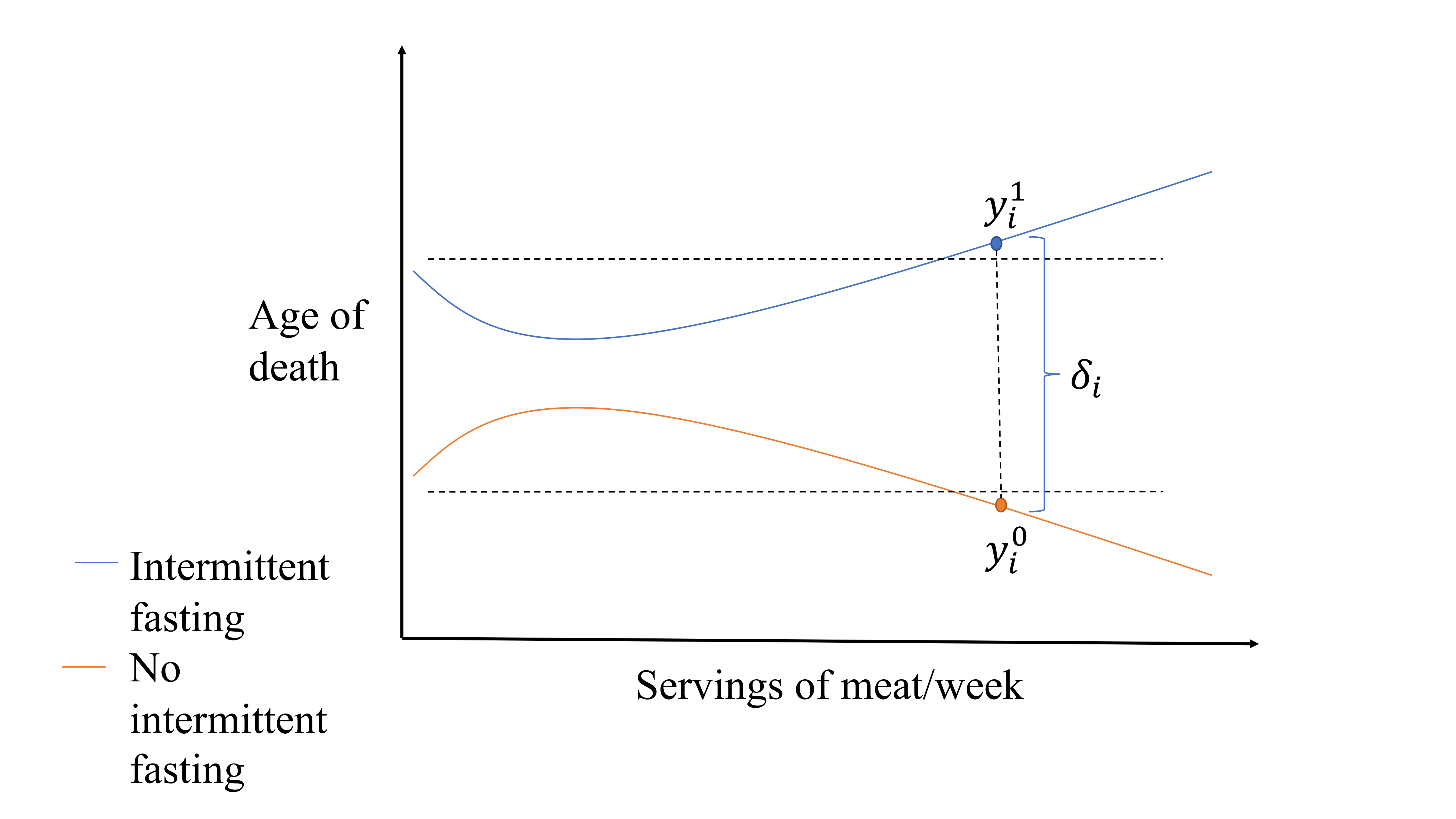


Y_i^1
$E[y_i|d_i = 1]$
Age of death
Y_i^0
$E[y_i|d_i = 0]$
Intermittent fasting
No intermittent fasting
Servings of meat/week



Age of death
y_i^1
δ_i
y_i^0
Intermittent fasting
No intermittent fasting
Servings of meat/week

The "fundamental reality of causal analysis" (Holland 1984): only observe y_i^1 **or** y_i^0



Causal Inference: Potential Outcomes

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- Potential outcomes: Y_i^1, Y_i^0
- Individ-level causal effect of treatment: $\delta_i = y_i^1 - y_i^0$
- Treatment: $D_i = 1$; Control: $D_i = 0$
- <u>Counterfactual outcome:</u> $E[Y_i^1 \mid D = 0], E[Y_i^0 \mid D = 1]$
- <u>Observed outcome:</u> $E[Y_i^0 \mid D = 0], E[Y_i^1 \mid D = 1]$

Test Your Understanding

What do each of the following represent?

$$E[Y_i^1 | D = 0]$$

$$E[Y_i^0 | D = 0]$$

$$E[Y_i^0 | D = 1]$$

$$E[Y_i^1 | D = 1]$$

Test Your Understanding

What do each of the following represent?

$E[Y_i^1 | D = 0]$ = Counterfactual outcome of control group

$E[Y_i^0 | D = 0]$ = Actual outcome of control group

$E[Y_i^0 | D = 1]$ = Counterfactual outcome of treatment group

$E[Y_i^1 | D = 1]$ = Actual outcome of treatment group

Why Do We Care About Counterfactuals?

- Because hypothetical counterfactual outcomes are not theoretically equivalent to the observed outcomes that we see in the real world mean(death| *observed* intermittent fasting = 1) - mean(death| *observed* intermittent fasting =0) = ?

N	Actual observed intermittent fasting	Observed age of death
1	1	60
2	0	65
3	1	70
4	0	80
5	0	80
6	1	75
7	0	90
8	1	80

mean(death| intermittent fasting had = 1) - mean(death| intermittent fasting had =0) = ?

N	y_i^0 Age of death if intermittent fasting had = 0	y_i^1 Age of death if intermittent fasting had = 1	Observed age of death
1	55	60	60
2	65	70	65
3	60	70	70
4	80	90	80
5	80	85	80
6	70	75	75
7	90	100	90
8	70	80	80

mean(death| *observed* intermittent fasting = 1) - mean(death| *observed* intermittent fasting =0)
71.25 - 78.75 = -7.5
mean(death| intermittent fasting had = 1) - mean(death| intermittent fasting had =0)
78.75 - 71.25 = 7.5

N	**Age of death if intermittent fasting had = 0**	**Age of death if intermittent fasting had = 1**	**Actual intermittent fasting**	**Observed age of death**
1	55	60	1	60
2	65	70	0	65
3	60	70	1	70
4	80	90	0	80
5	80	85	0	80
6	70	75	1	75
7	90	100	0	90
8	70	80	1	80

Observed outcomes in the real world are not necessarily the same as potential outcomes

Observed outcomes can yield the opposite conclusion as the potential outcomes would have given us

$$E[Y_i^1 \mid D = 1] - E[Y_i^0 \mid D = 0]$$
$$\neq$$
$$E[Y_i^1 \mid D = 1] - E[Y_i^0 \mid D = 1]$$

GOAL:

$$E[Y_i^1 \mid D = 1] - E[Y_i^0 \mid D = 0] = E[Y_i^1 \mid D = 1] - E[Y_i^0 \mid D = 1]$$

Difference between treatment and control group outcomes

Difference between a group's actual outcome and counterfactual outcome

Law of Large Numbers

- As N increases, sample average = average of population
- Randomization => drawn from same population
- Average of a randomized group A/B will = average of population if N is big enough
- Actual outcome for treatment group = Counterfactual outcome for control group

$$E[Y_i^1 \,|\, D_i = 1] = E[Y_i^1 \,|\, D_i = 0]$$

LLN: Observed outcome for treated group = Counterfactual outcome for control group

$$E[Y_i^1 \mid D_i = 1] = E[Y_i^1 \mid D_i = 0]$$

ATE = Difference in average expected outcomes:

$$E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] = E[Y_i^1 \mid D_i = 1] - E[Y_i^0 \mid D_i = 0]$$

$$E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] = E[Y_i^1 \mid D_i = 0] - E[Y_i^0 \mid D_i = 0]$$

$$E[Y_i \mid D = 1] - E[Y_i \mid D = 0] = E[Y_i^1 \mid D = 0] - E[Y_i^0 \mid D = 0]$$

Experimental outcome

Counterfactual outcome - Actual outcome

Summary of Potential Outcomes and Experiments

- Idealized world: $E[Y_i^1 | D=0] - E[Y_i^0 | D=0]$
- Randomization: $E[Y_i^0 | D=1] = E[Y_i^0 | D=0]$

$$E[Y_i^1 | D=1] - E[Y_i^0 | D=0] = E[Y_i^1 | D=0] - E[Y_i^0 | D=0]$$

Experimental outcome

Counterfactual outcome - Actual outcome

Check Your Understanding

- What would an ideal experiment look like if we lived in a hypothetical world?
- What does the Law of Large Numbers tell us?
- What does the LLN tell us in terms of counterfactual and observed outcomes?
- How does this lead us to believe that randomization yields causal inference?

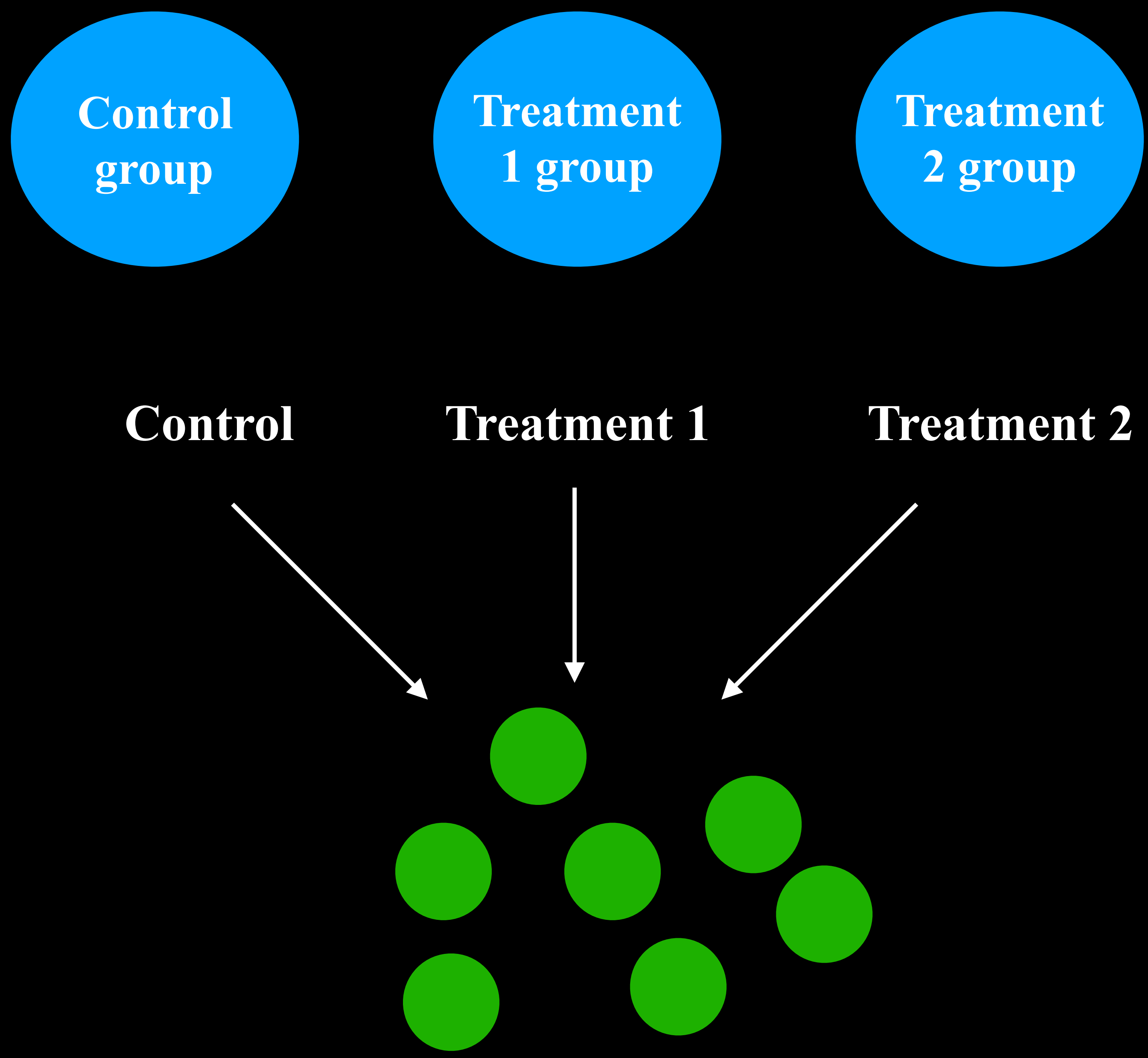
Questions?

Sources

- Morgan and Winship, *Counterfactuals and Causal Inference* (2007)
- Angrist and Pischke, *Mastering Metrics* (2015)
- Rubin (2005)
- Pearl, *Causality* (2000)

Experimental Design and Implementation

Between and Within Subject Designs



Findings of Differences Between Between and Within Studies

- Differences in magnitude (Gneezy 2005)

% Subjects Considering It Very Unfair

	Low Cost Lie	High Cost Lie	Difference
Between	36%	62%	24%
Within	18%	68%	50%

Findings of Differences Between Between and Within Studies

- But also differences of effect (Fox and Tversky 1998)

	Clear Odds Gamble	Vague Odds Gamble
Between	No ambiguity aversion	
Within	Ambiguity aversion	

Range, Context, Carryover, Order Effects

% Subjects Considering It Very Unfair

	Low Cost Lie	High Cost Lie	Difference
Between	36%	62%	26%
Within	18%	68%	50%

Within Subjects, Counterbalanced

	Low Cost Lie	High Cost Lie
Low-cost first	?	?
High cost first	?	?

Symmetric Carryover Effects

	Low Cost Lie	High Cost Lie	Difference (high - low)
Low cost first, high cost second	$\boxed{36\%}$	66%	30
Low cost second, high cost first	40%	$\boxed{62\%}$	22
Difference (first - second)	-4	-4	0
Counterbalanced mean	38	64	$\boxed{26}$

Symmetric Carryover Effects

	Low Cost Lie	High Cost Lie	Difference (high - low)
Low cost first, high cost second	36%	66%	30
Low cost second, high cost first	40%	62%	22
Difference (first - second)	-4	-4	0
Counterbalanced mean	38	64	26
Between subject design	36	62	26

Symmetric Carryover Effects

	Treatment A	Treatment B	Difference (high - low)
A first, B second	$\boxed{\mu_1}$	$\mu_2 + k$	$\mu_2 + k - \mu_1$
A second, B first	$\mu_1 + k$	$\boxed{\mu_2}$	$\mu_2 - \mu_1 - k$
Difference (first - second)	$-k$	$-k$	0
Counterbalanced mean	$\mu_1 + \frac{k}{2}$	$\mu_2 + \frac{k}{2}$	$\boxed{\mu_2 - \mu_1}$
Between subject design	μ_1	μ_2	$\boxed{\mu_2 - \mu_1}$

Asymmetric Carryover Effects

	Low Cost Lie	High Cost Lie	Difference (high - low)
Low-cost first, high cost second	36%	74%	42
Low cost second, high cost first	4%	62%	58
Difference (first - second)	32	-12	40
Counterbalanced mean	20	68	48
Between subject design	36	62	26

Asymmetric Carryover Effects

	Treatment A	Treatment B	Difference (high - low)
A first, B second	$\boxed{\mu_1}$	$\mu_2 + r$	$\mu_2 + r - \mu_1$
A second, B first	$\mu_1 + k$	$\boxed{\mu_2}$	$\mu_2 - \mu_1 - k$
Difference (first - second)	$-k$	$-r$	$-r + k$
Counterbalanced mean	$\mu_1 + \frac{k}{2}$	$\mu_2 + \frac{r}{2}$	$\boxed{\mu_2 + \frac{r}{2} - \mu_1 - \frac{k}{2}}$
Between subject design	μ_1	μ_2	$\boxed{\mu_2 - \mu_1}$

Would You Need to Be Concerned?

	Treatment A	Treatment B	Difference (high - low)
A first, B second	3	3	
A second, B first	1	5	
Difference (first - second)			
Counterbalanced mean			
Between subject design	3	5	2

Would You Need to Be Concerned? No.

	Treatment A	Treatment B	Difference (high - low)
A first, B second	3	3	0
A second, B first	1	5	4
Difference (first - second)	2	2	0
Counterbalanced mean	2	4	2
Between subject design	3	5	2

Within Subject Designs

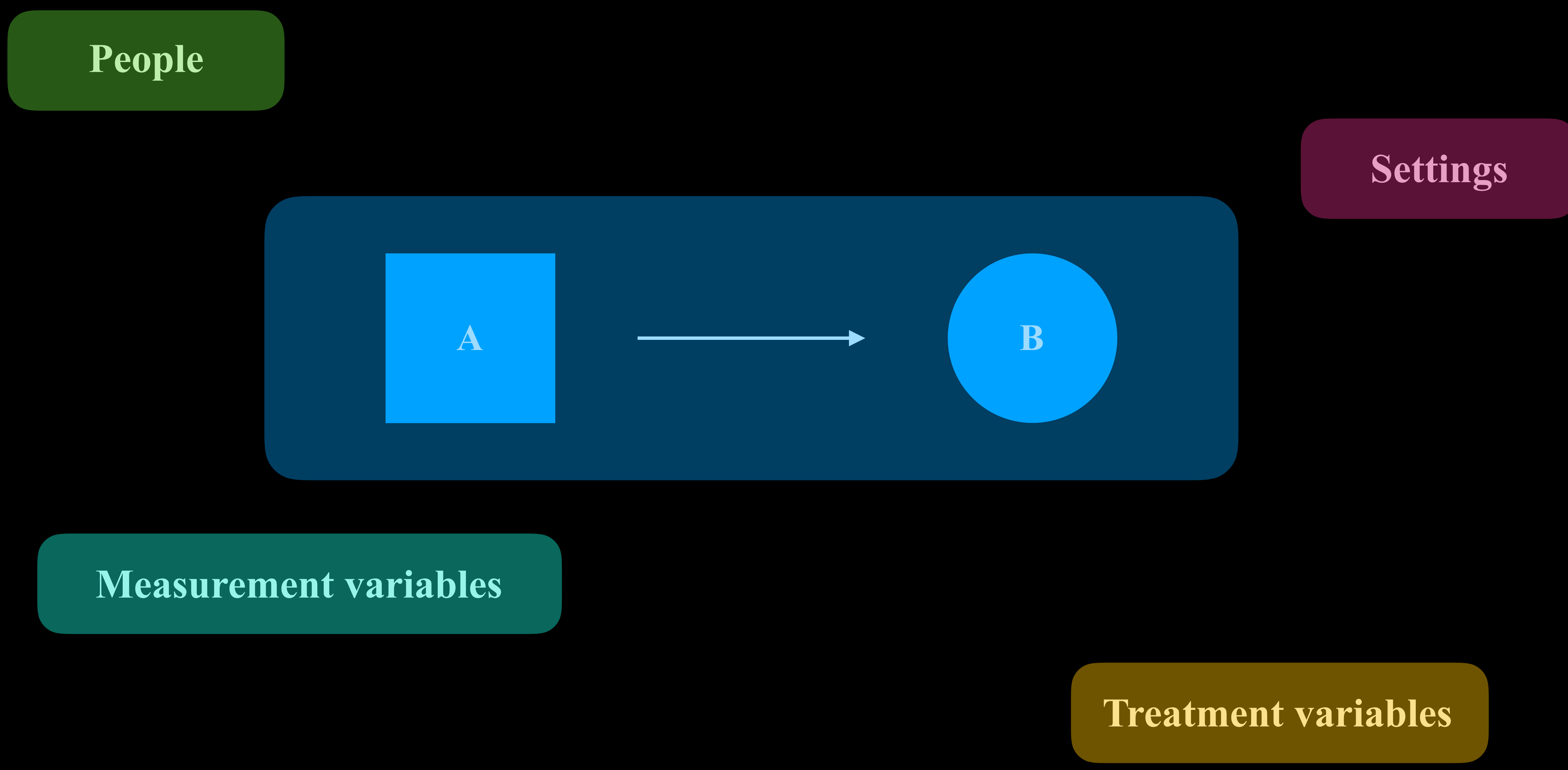
- Asymmetric context effects and carryover effects
- Participants may guess purpose of experiment
- Increase statistical power
- All covariates held constant

Between Subject Designs

- No range/carryover/ order effects
- Purpose hidden from participants
- Need twice the number of participants
- Possibility that covariates are not equal between treatment groups

Internval vs. External Validity

Internal vs. External Validity



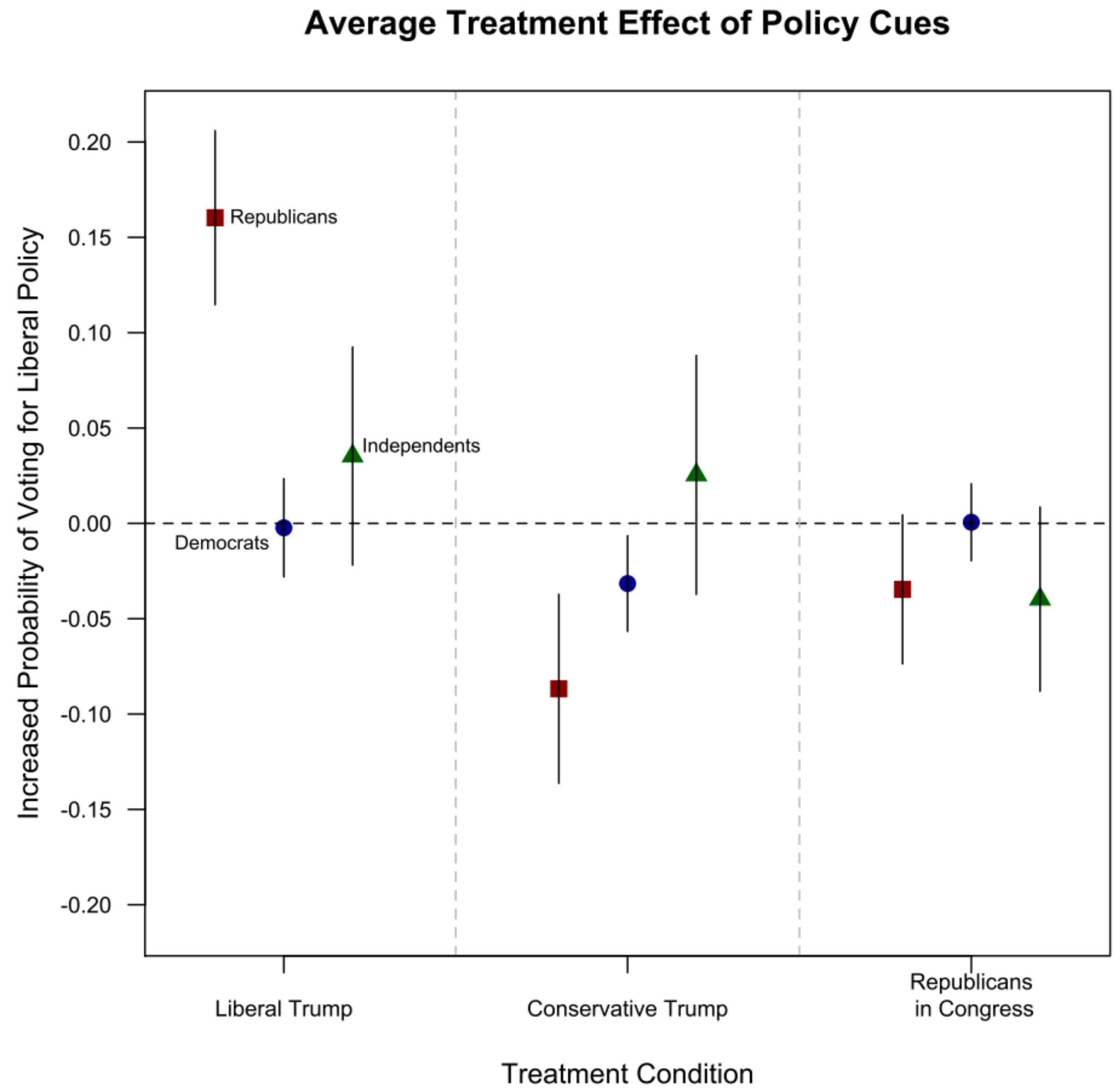
External Validity

Smoking —> lung cancer in:

- A breed of rabbits of a certain age
- In the 1950s
- Using one type of cigarette

Trump's position —> subjects' positions

FIGURE 1. Average Treatment Effect Across Issues



Note: The effects indicate the average movement within groups and by treatment condition. Republicans are the only group that seems to shift positions significantly, and only in relation to Donald Trump cues. But it is true that they react in both a liberal and a conservative direction depending upon the cue.

Barber and Pope 2019

External Validity Questions

- What about with a Dem. leader?
- Different issues? Issue salience?
- Different politicians?
- Different measures of issue support? Likert scale?
- Exclusion of "don't know" as answer option?
- How long do effects last?

Tradeoff: Internal for External Validity (Jenke & Krosnick, working paper)

- Run 1 week before Biden chose Harris
- Test: Does the race and sex of the VP impact voting intentions?
- 6 Black female candidates, 5 white female candidates, 1 Black male candidate (Booker), 1 white male candidate (O'Rourke)
- External validity: Real candidates, timely
- Internal validity: >1 possible cause, prospective turnout

Susan Rice may be selected to run for Vice-president of the United States with Joe Biden this year.

- Ms. Rice was U.S. National Security Advisor from 2013 to 2017. She was also U.S. Ambassador to the United Nations from 2009 to 2013, in addition to working in the U.S. State Department and for the National Security Council.
- Prior to her political career, Ms. Rice worked as a management consultant at McKinsey & Company from 1990 to 1992.
- Ms. Rice has no known religious affiliation; she attended a private Episcopal high school in Washington, D.C.
- She was born and raised in Washington, D.C.

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External Validity and Data Sources

Is your sample and the target population the same in terms of covariates that moderate/mediate the relationship?

- Probability sample: target population members have a known, non-zero random probability of being selected (TESS, IPSOS)

- Convenience samples: MTurk, Lucid, undergraduates

- Student samples and non-college samples (Druckman and Kam 2011):

  - Similar: Partisanship, ideology, importance of religion, belief in limited government, views on homosexuality and immigrants, social trust, extent of following/discussing politics, general media use

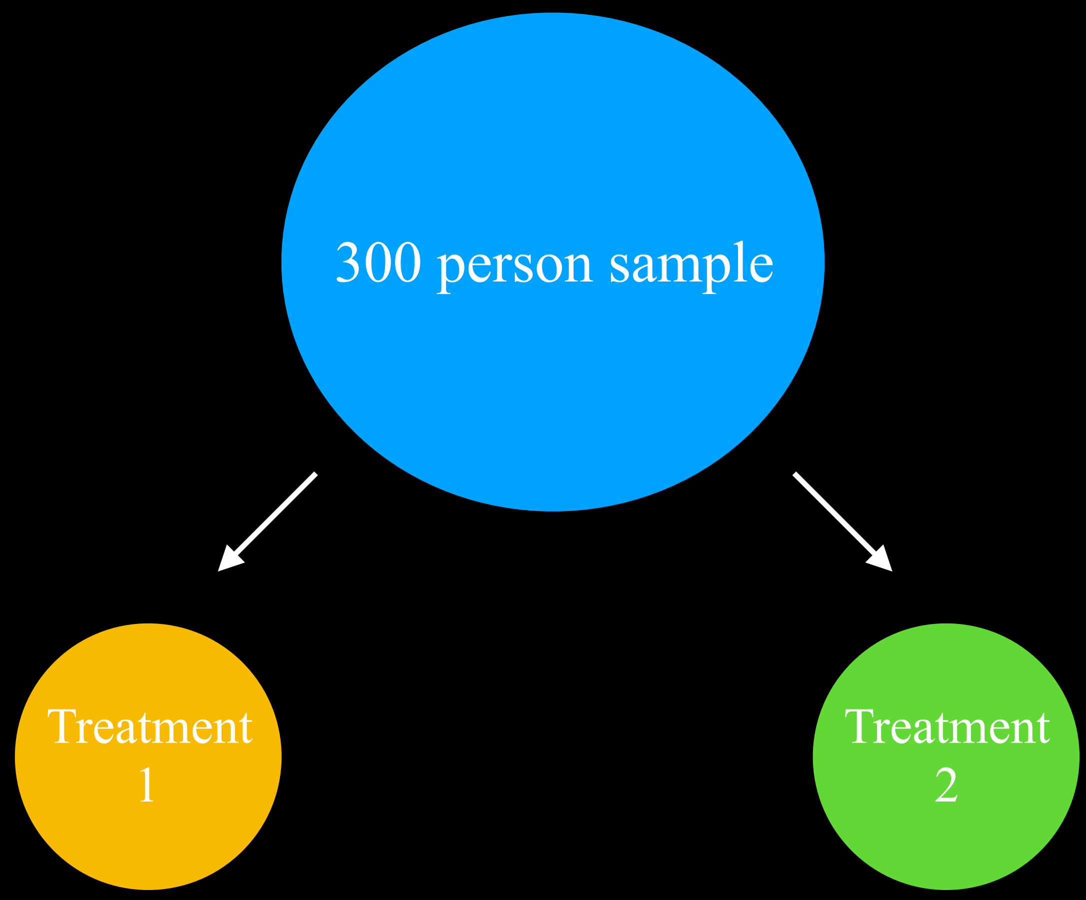
  - Not similar: religious attendance, education level, age, political information, racial attitudes

- MTurk and . . .
  - CCES: similar occupations and geographic locations (Huff and Tingley 2015)
  - U.S. population
    - More women, fewer African Americans (Kahan 2013)
    - More liberals, more young people, more educated people (Huff and Tingley 2015)
    - Fewer married people (Berinsky et al. 2012, Shapiro et al. 2013)
    - More lower income people, more unemployed (Shapiro et al. 2013)
    - More LGBT people (Corrigan et al. 2015)

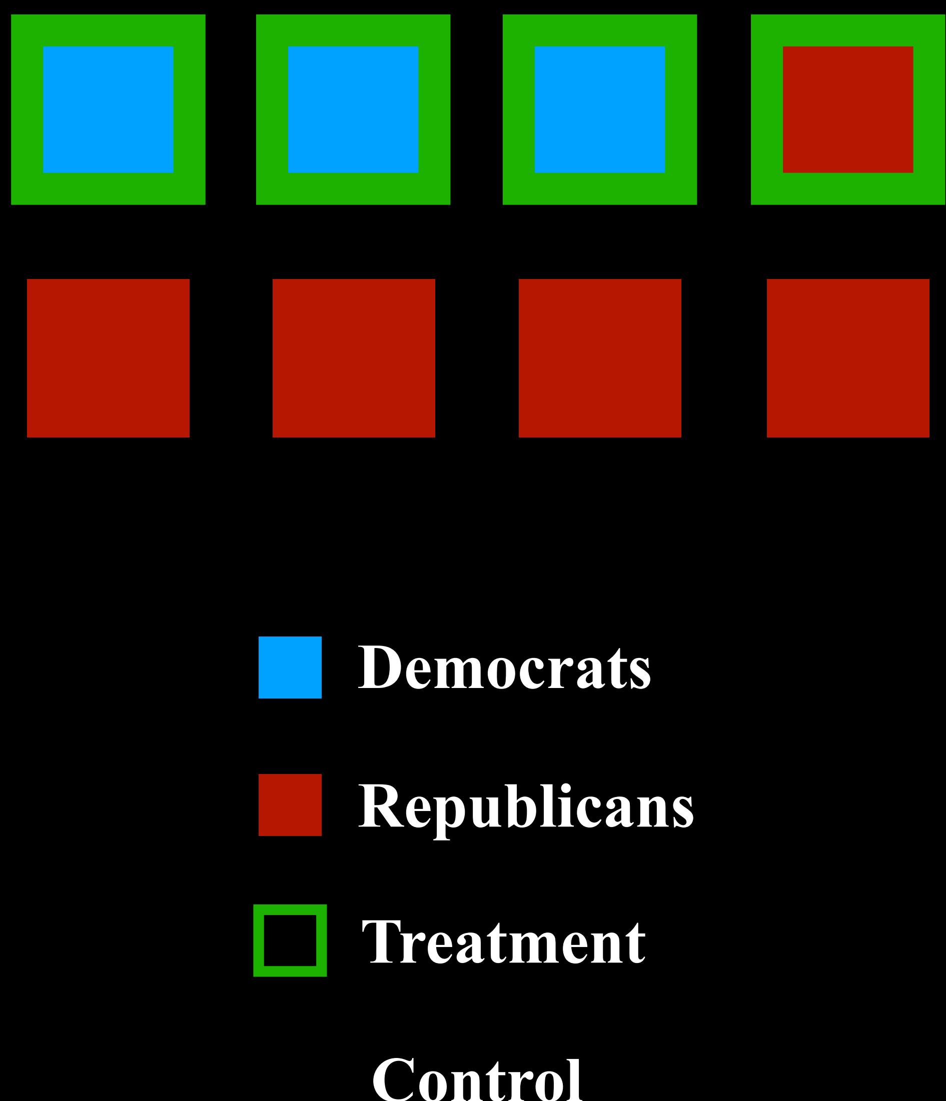
Internal Validity, Confounds, and Randomization Checks

***Ex ante*, randomization balances covariates between treatment and controls. *Ex post*, it may not.**

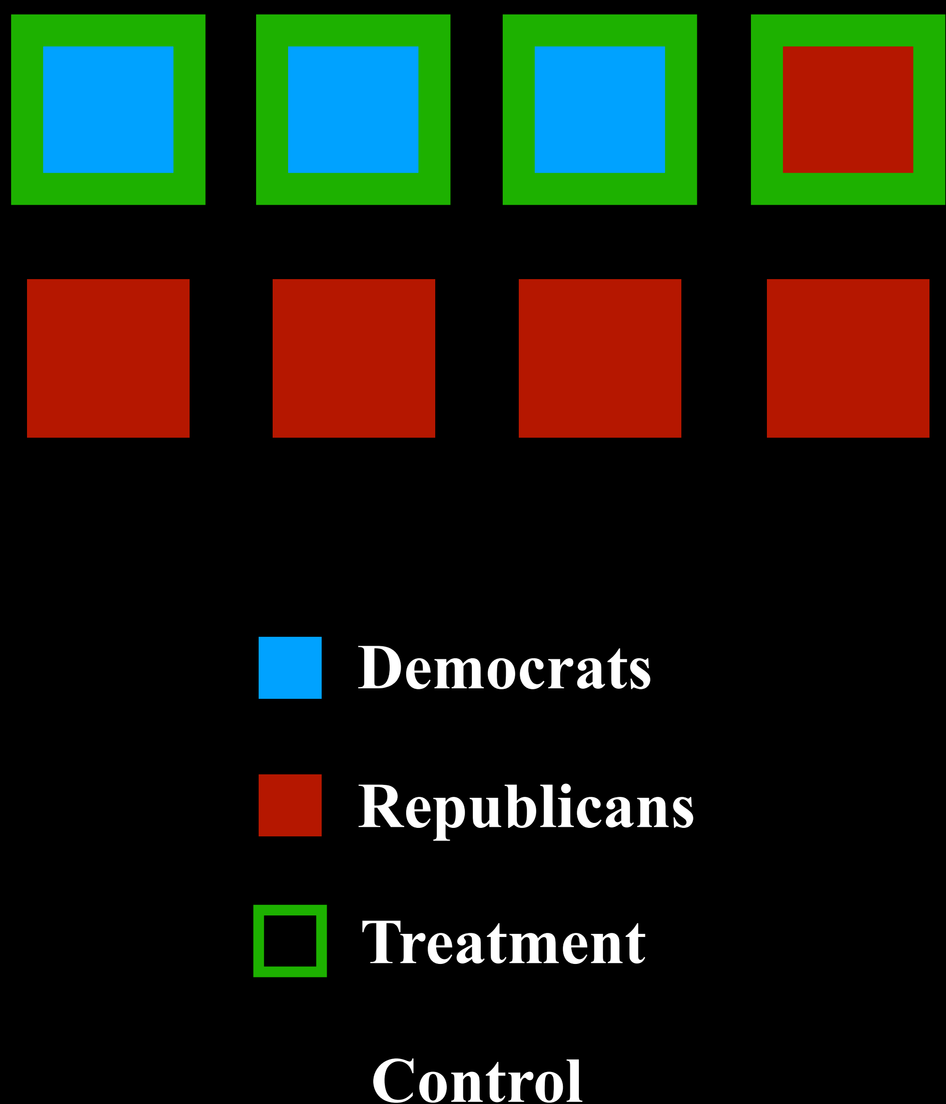
Why Does Randomization Work?



H1: People rate female candidates lower on likability scales because they are female
Treatment 1: male candidate
Treatment 2: female candidate

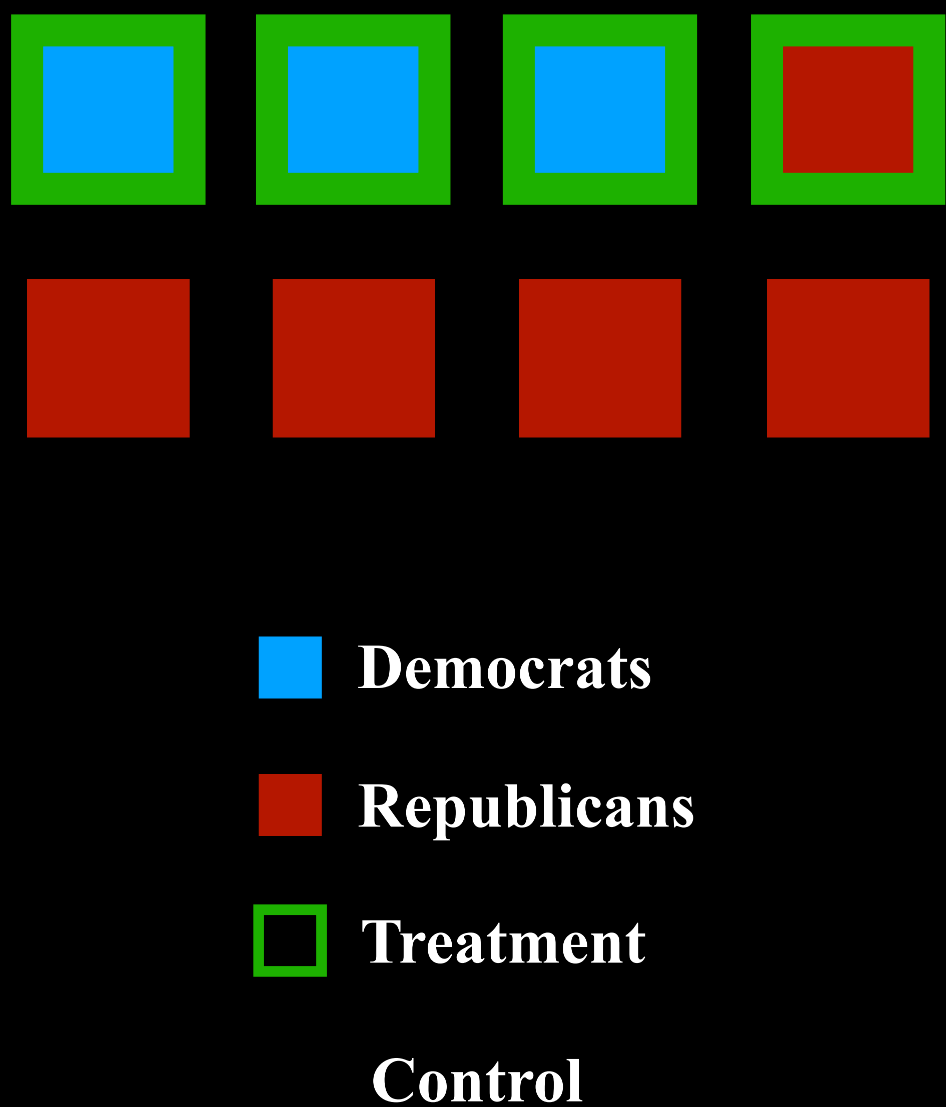

Democrats
Republicans
Treatment
Control

$$Y = a + \beta_1(Treatment) + e_i$$



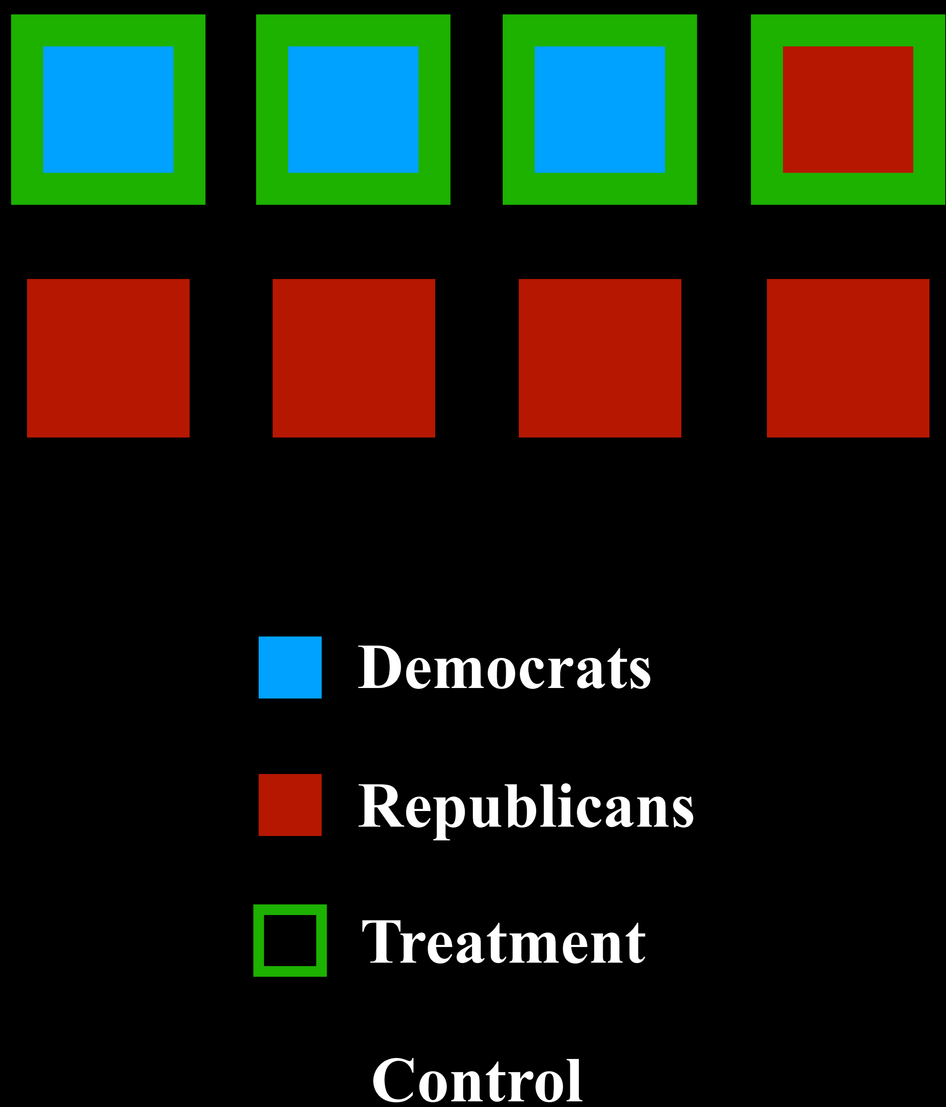
Treatment effect	Democrat	β_1
No effect	+	
+	+	
+	-	

$$Y = a + \beta_1(Treatment) + e_i$$



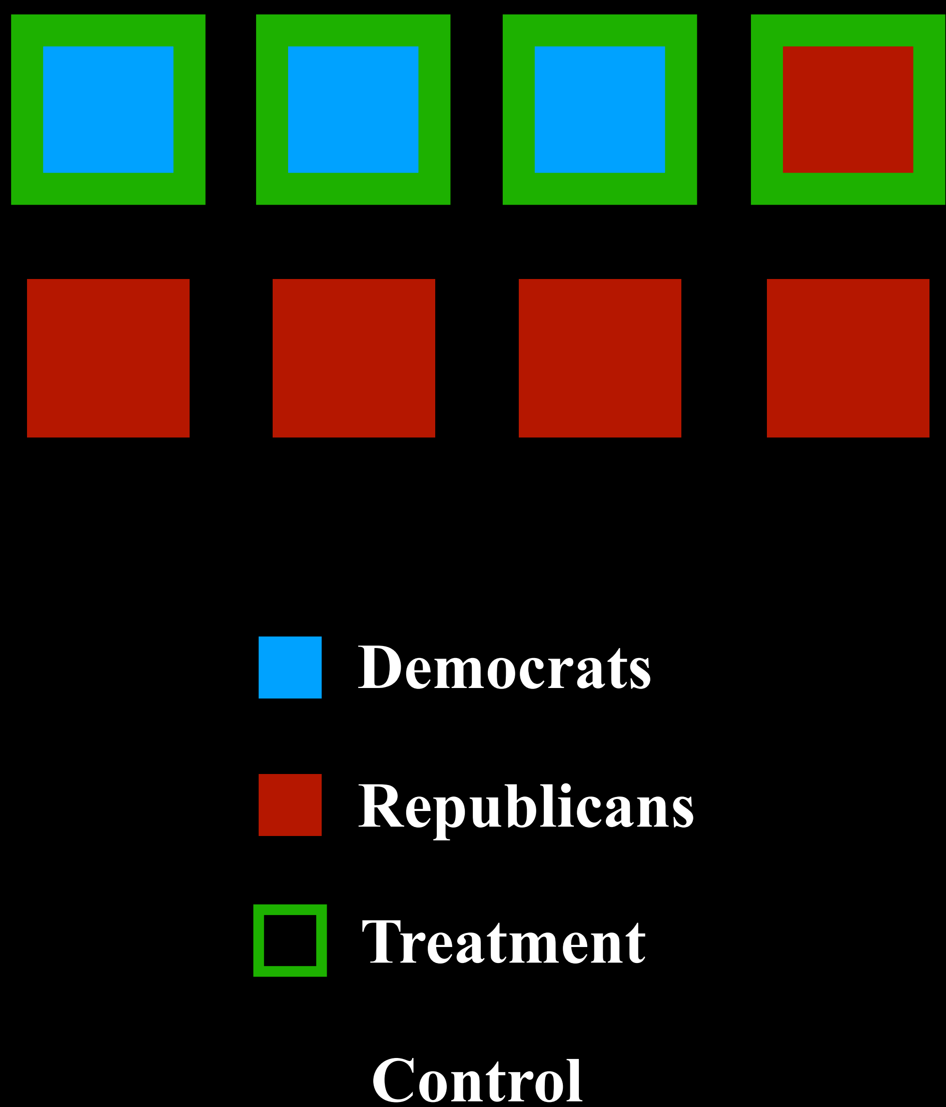
Treatment effect	**Democrat**	β_1
No effect	+	+
+	+	
+	-	

$$Y = a + \beta_1(Treatment) + e_i$$



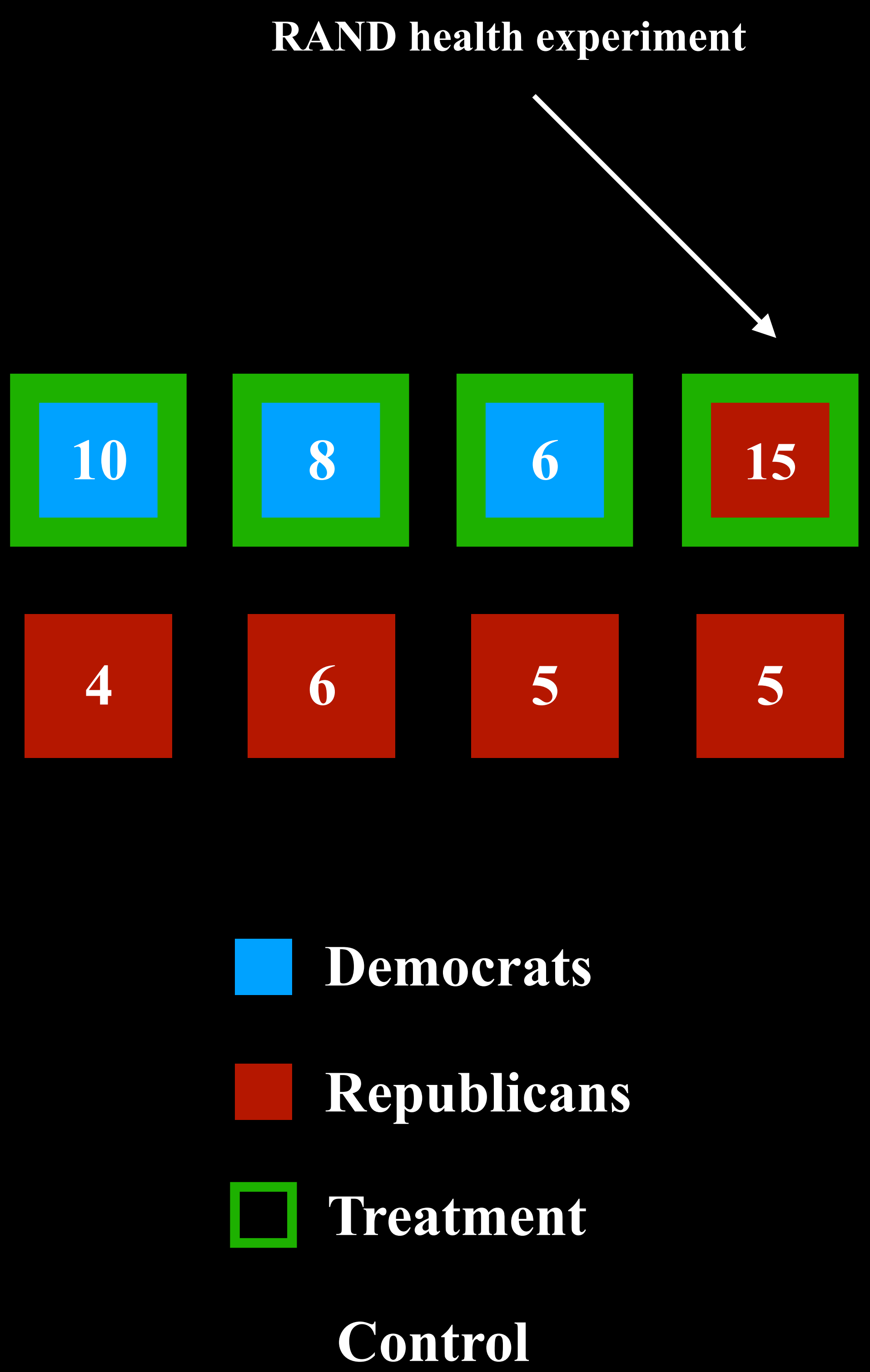
Treatment effect	Democrat	β_1
No effect	+	+
+	+	Bigger +
+	-	

$$Y = a + \beta_1(Treatment) + e_i$$



Treatment effect	**Democrat**	β_1
No effect	+	+
+	+	Bigger +
+	-	?

1. Balance test
2. Include party as a covariate



$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$

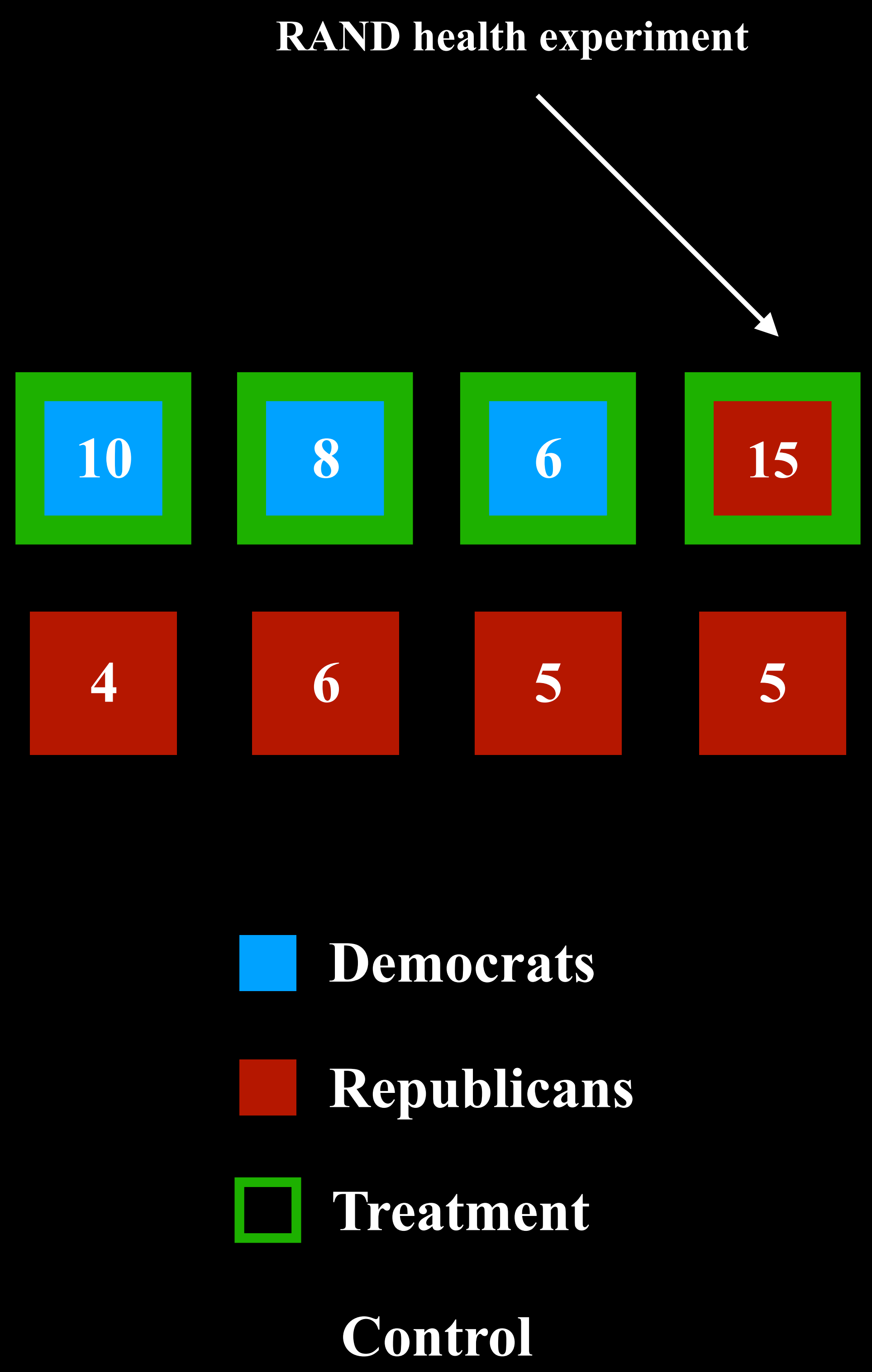
Treatment effect	Democrat	β_1	β_2
No effect	+, sig.		

Edit Browse

var6[13]

	treat	party	dv
1	1	1	10
2	1	1	8
3	1	1	6
4	1	0	15
5	0	0	4
6	0	0	6
7	0	0	5
8	0	0	5
9	1	1	10
10	1	1	8
11	1	1	6
12	1	0	15
13	0	0	4
14	0	0	6
15	0	0	5
16	0	0	5
17	1	1	10
18	1	1	8
19	1	1	6
20	1	0	15
21	0	0	4
22	0	0	6
23	0	0	5
24	0	0	5
25	1	1	10
26	1	1	8
27	1	1	6
28	1	0	15
29	0	0	4
30	0	0	6

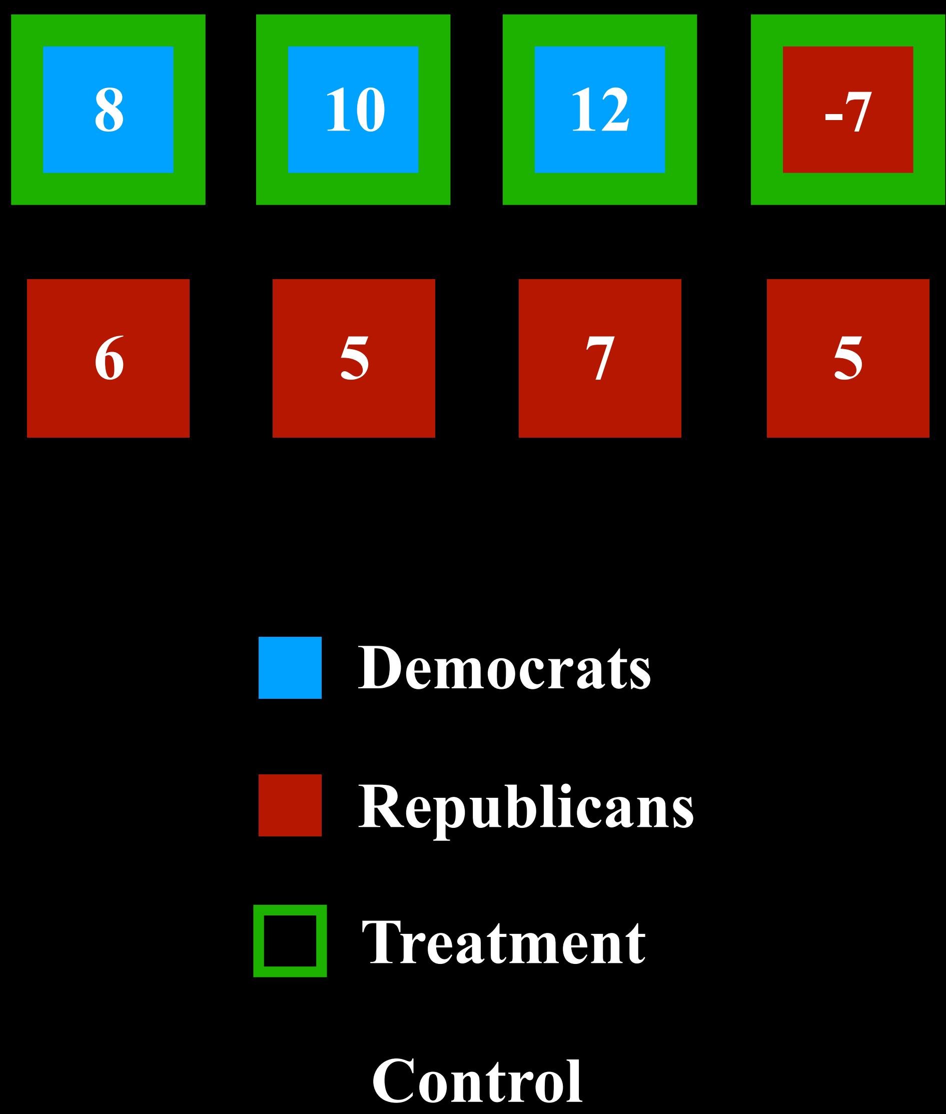
Vars: 3 Order: Dataset Obs: 144



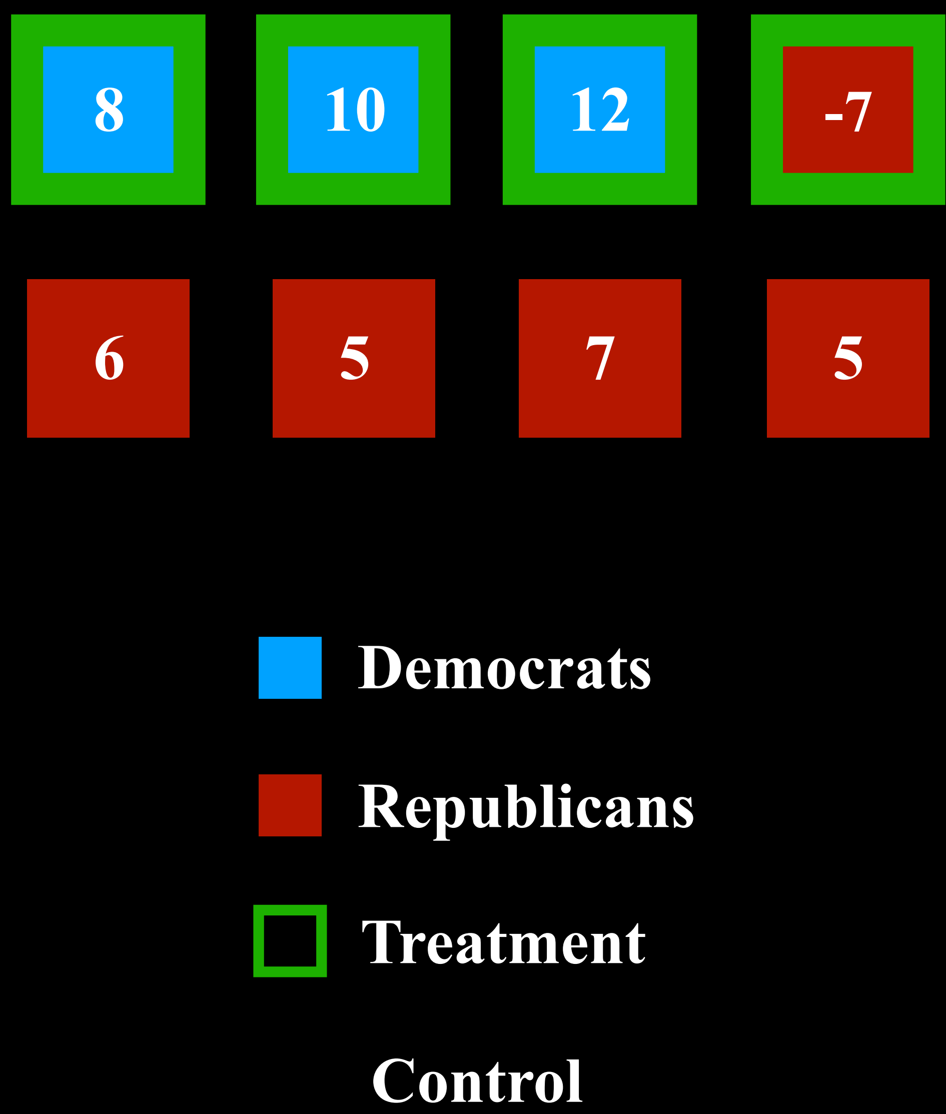
$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$

Treatment effect	Democrat	β_1	β_2
No effect	+, sig.	10 (p<0.001)	-7 (p<0.001)

$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$



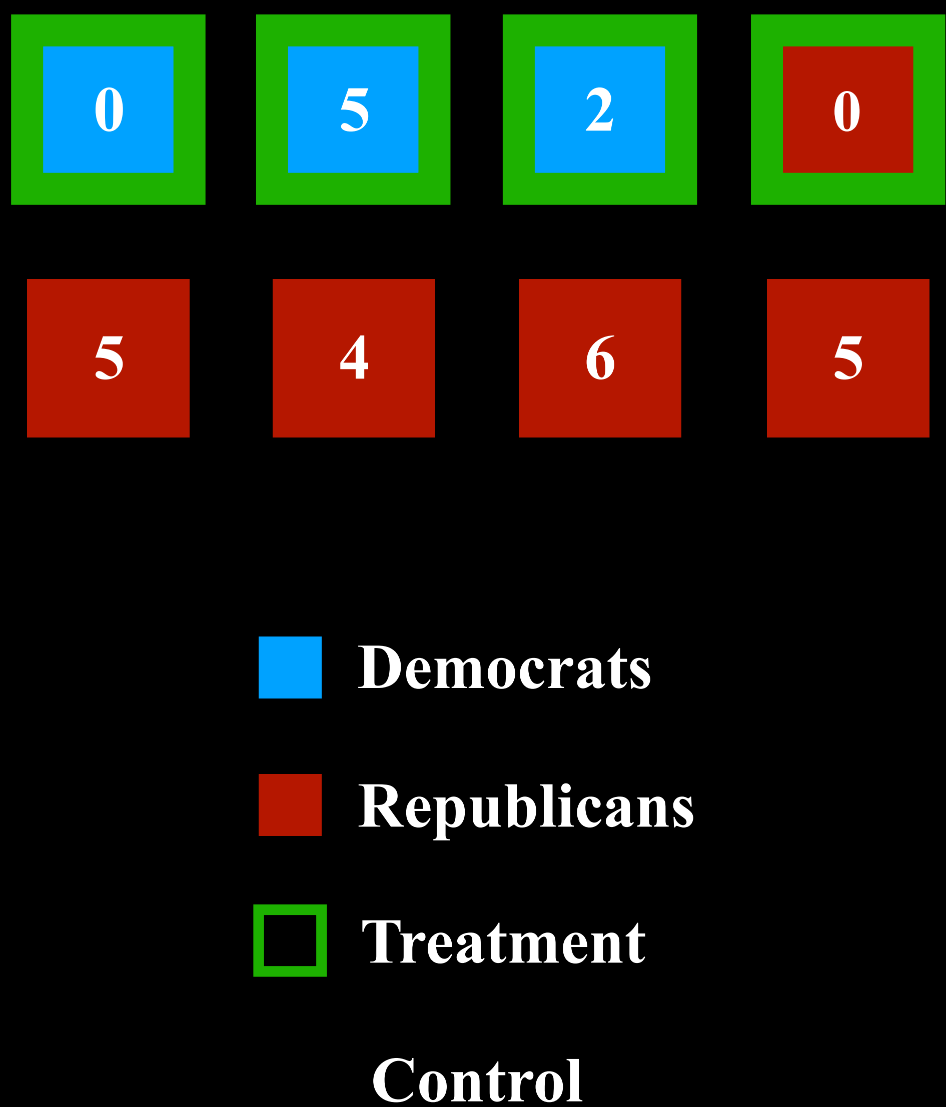
Treatment effect	**Democrat**	β_1	β_2
+, sig.	+, sig.		



$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$

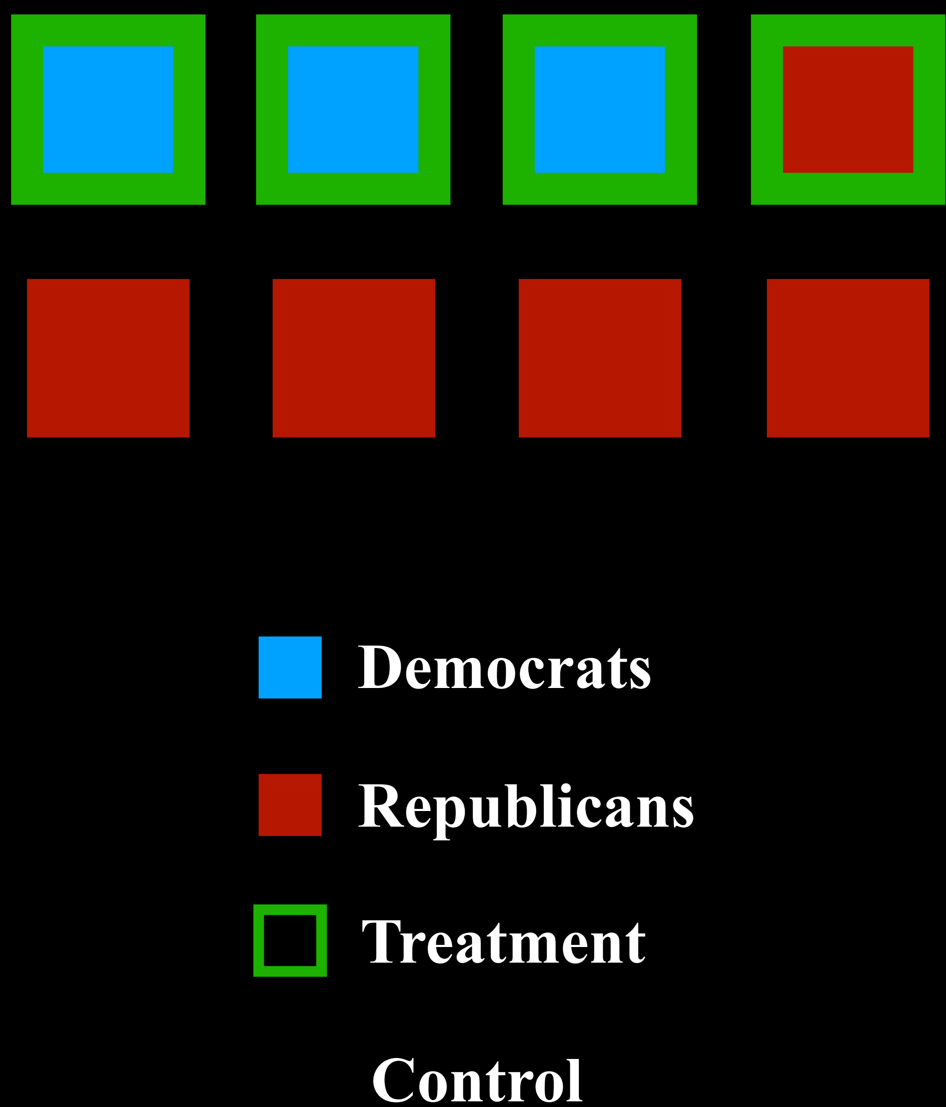
Treatment effect	**Democrat**	β_1	β_2
+, sig.	+, sig.	-12.75 (p<0.001)	17 (p<0.001)

$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$



Treatment effect	Democrat	β_1	β_2
+, sig.	-, sig.	-5 (p<0.001)	2.33 (p<0.001)

$$Y = a + \beta_1(Treatment) + \beta_2(Democrat) + e_i$$



Treatment effect	Democrat	β_1	β_2
No effect	+, sig.	?	?
+, sig.	+, sig.	?	?
+, sig.	-, sig.	?	?

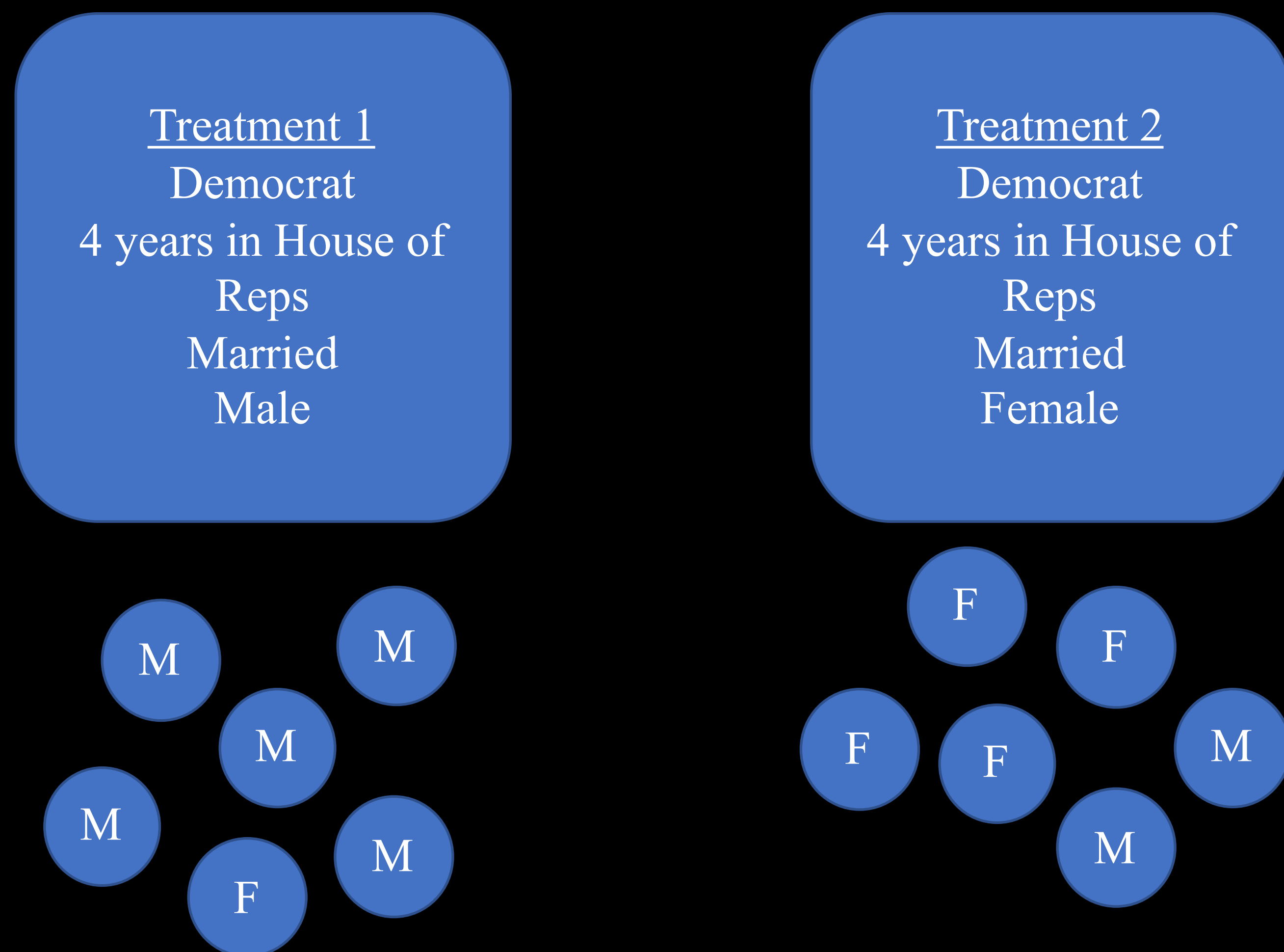
Chance that it gets it right depends on variance on d.v. | Party affiliation

Balance and Randomization Checks

- Can find out if your randomization “worked”. . . but that’s it
- Adding in covariates does not necessarily solve the problem (and you don’t know if it does)
  - Large *N* doesn’t solve the issue
- Report balance tables on variables that theoretically matter
- The fix: <u>replication</u>
- Foresight: Block on the variable

Blocking

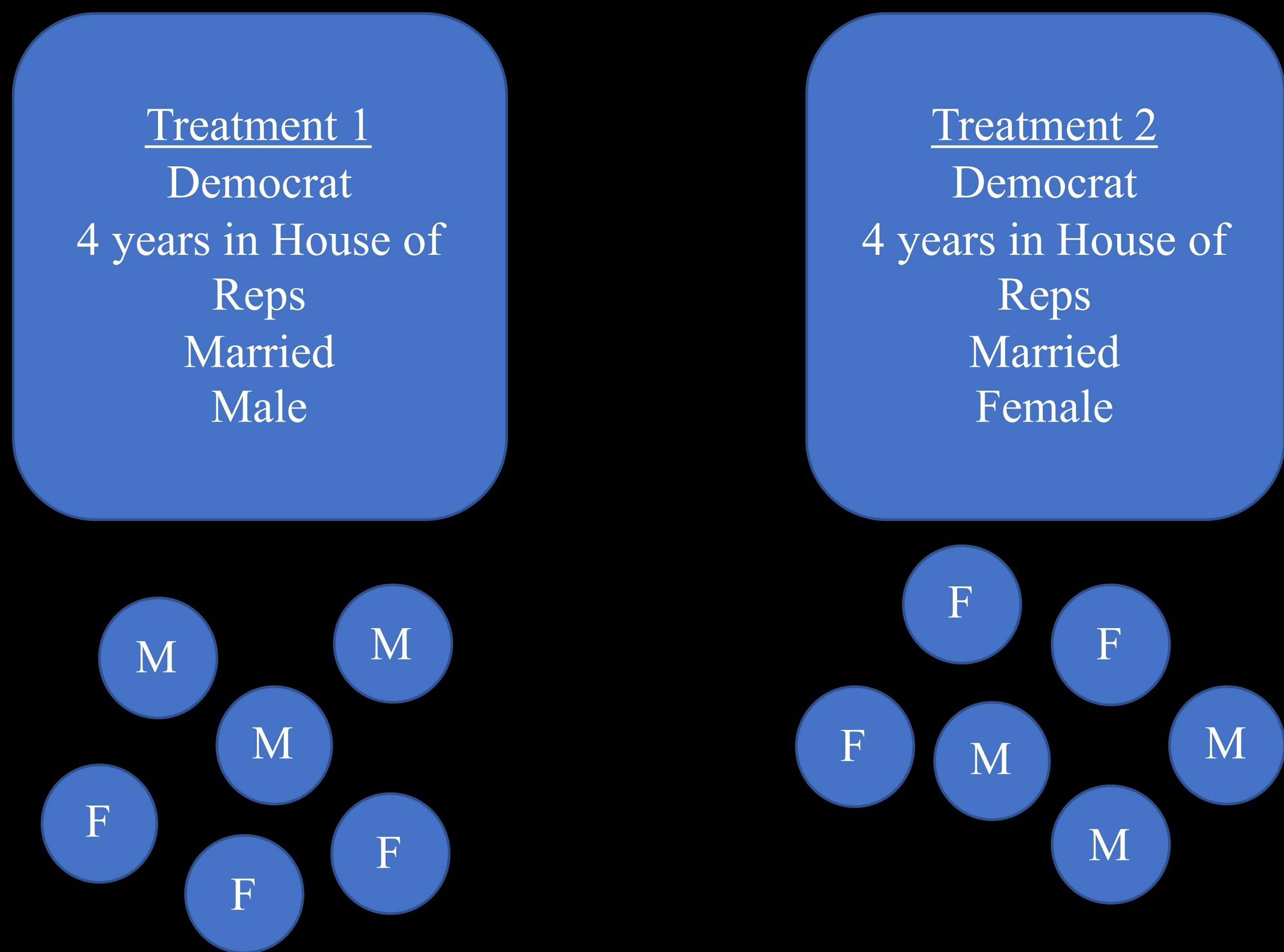
Example Experiment



Block on respondent gender:

1. **Separate male and female respondents**
2. **Randomly assign treatment conditions within gender**

Example Experiment



Block on respondent gender:

1. **Separate male and female respondents**
2. **Randomly assign treatment conditions within gender**

Questions for Breakout Rooms (15 min.)

- Is the design of the experiment (between vs. within) the best design? (Take into account potential context/carryover effects, ease of guessing purpose of experiment)

- Theoretically, are there any important variables that will confound the experiment if not effectively randomized?

    - If so, can you use a blocked design?

- How is the external validity of the experiment? What types of real-world situations will it apply to, and which will it not?

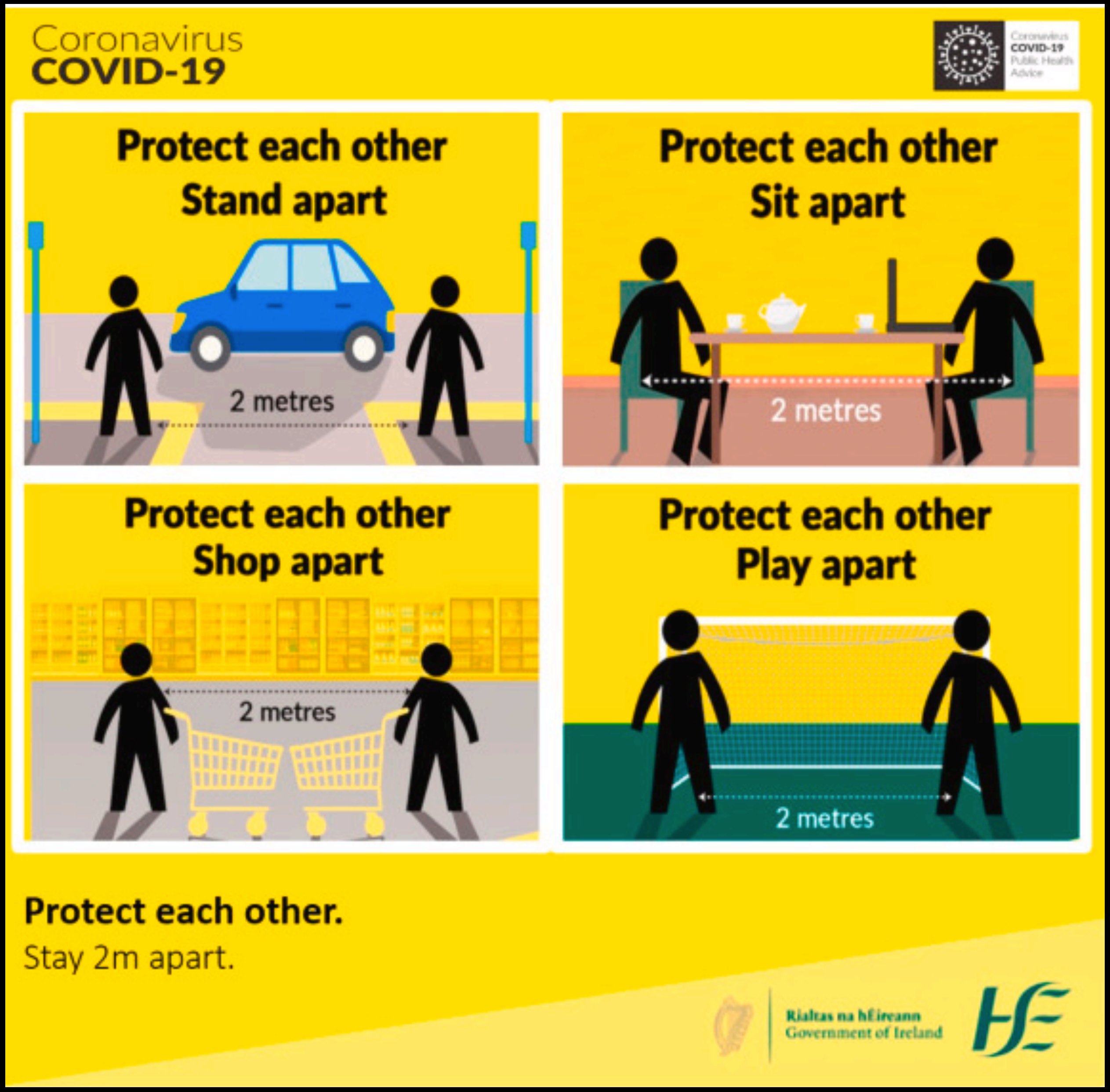
- Is your data source likely to limit the external validity of your experiment?

Questions?

Conjoint Experiments

Treatment mechanism = ?

Control



Treatment

Lunn et al., 2020

Conjoint Experiments

- Vary more than one aspect of the treatment
- Identify aspect-specific changes in d.v.
- Within subject, repeated measures design

	Candidate A	Candidate B
Gender	Male	Female
Occupation	Lawyer	Activist
Gun Control	Strongly oppose	Weakly support
Political party	Independent	Republican
Age	53	77

Table 1: List of Attributes and Values for Conjoint Experiment

Attribute	**Values**
Age	37, 45, 53, 61, 77
Gender	Female, Male
Race/Ethnicity	White, Hispanic/Latino, Black, Asian American, Native American
Previous Occupation	Business executive, College professor, Lawyer, Doctor, Activist
Military Service Experience	Did not serve, Served in the Army, Served in the Navy, Served in the Marine Corps, Served in the Air Force
Prior Political Experience	Mayor, Governor, U.S. Senator, U.S. Representative, No prior political experience
Party	Democrat, Republican, Independent
Religion	Catholic, Evangelical Protestant, Mainline Protestant Mormon, Jewish
Position on Same-Sex Marriage	Strongly support, Support, Oppose, Strongly oppose
Position on Tax Raise for Wealthy	Strongly support, Support, Oppose, Strongly oppose
Position on Gun Control	Strongly support, Support, Oppose, Strongly oppose

ATEs Not Possible

- 5x2x5x5x5x5x3x5x4x4x4 = 6,000,000 possible unique profiles
- 30 profiles x 500 respondents = 15,000

AMCE (Average Marginal Component Effect)

- ATE: Republican vs. Democratic candidate: Average probability that candidate A is chosen if he/she is a Republican candidate - average probability that candidate A is chosen if he/she is a Democratic candidate
- Random assignment of values for each attribute
- Other attributes = pre-treatment covariates
- Calculate AMCEs by:
  - Differences in d.v. between attribute values
  - Linear regressions - other attribute values as dummies, tested value as baseline

Conjoint Design

- 1-3 profiles
- # attributes
  - Too few — masking
  - Too many — cognitive burden
  - Jenke et al. (2021): 5, 8, and 11
- Probabilities of each attribute value — uniform or weighted
  - Results unique to each randomization distribution
- Randomize order of attributes

	Candidate A	Candidate B
Gender	Male	Female
Occupation	Lawyer	Activist
Gun Control	Strongly oppose	Weakly support
Political party	Independent	Republican
Age	53	77

	Candidate A	Candidate B	Candidate C
Political party	Republican	Democrat	Democrat
Gender	Female	Female	Male
Gun Control	Weakly support	Weakly oppose	Strongly oppose
Political experience	No prior political experience	U.S. Senator	U.S. Senator
Occupation	Activist	Lawyer	Business executive
Religion	Jewish	Mainline Protestant	Evangelical Protestant
Military service	Served in the Air Force	Served in the Navy	Did not serve
Same-sex marriage	Weakly support	Weakly oppose	Strongly oppose
Increase wealthy's tax	Weakly support	Weakly oppose	Strongly oppose
Age	77	53	45
Race	Black	Hispanic/Latino	Asian American

Conjoint Design

- 1-3 profiles
- # attributes
  - Too few — masking
  - Too many — cognitive burden
  - Jenke et al. (2020): 5, 8, and 11 and bounded rationality
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Conjoint Design

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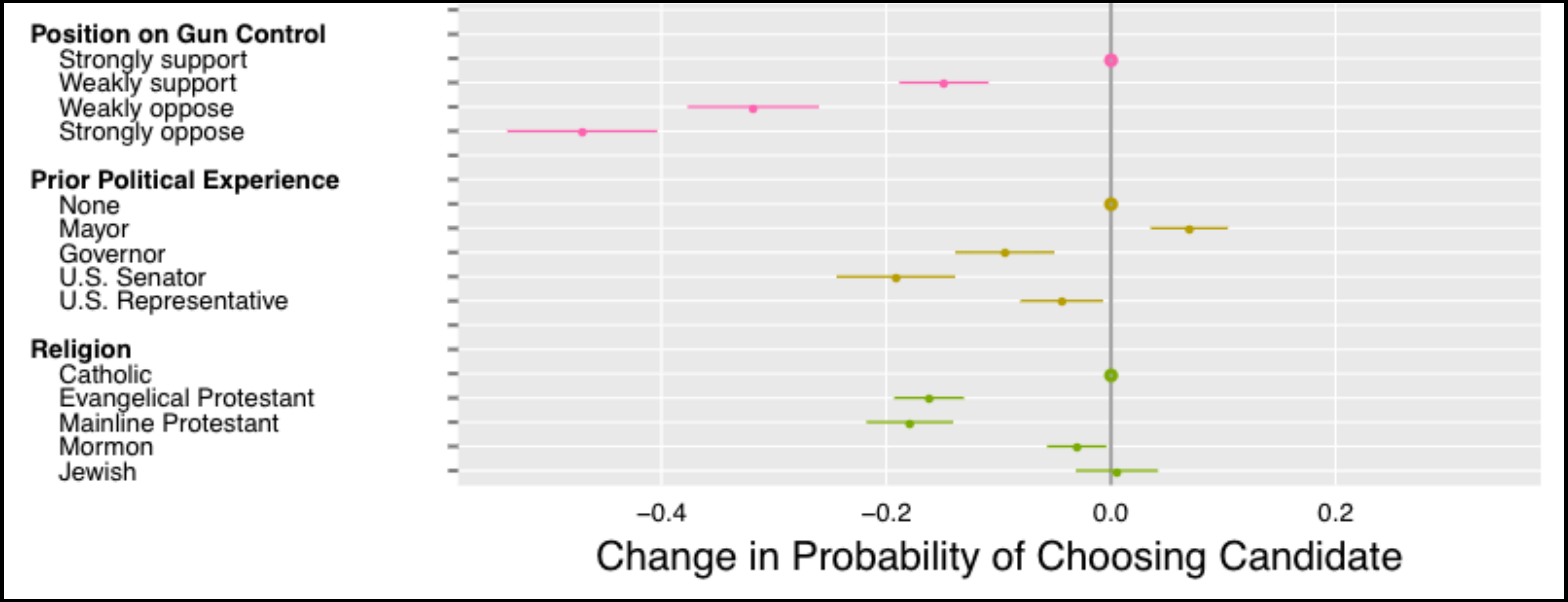
  - Results unique to each randomization distribution
- Randomize order of attributes

Interpretation

- Reference value
- Average value



<u>**Interpretation**</u>

- **Reference value**
- **Average value**

Figure 2: AMCEs in the Pooled Data

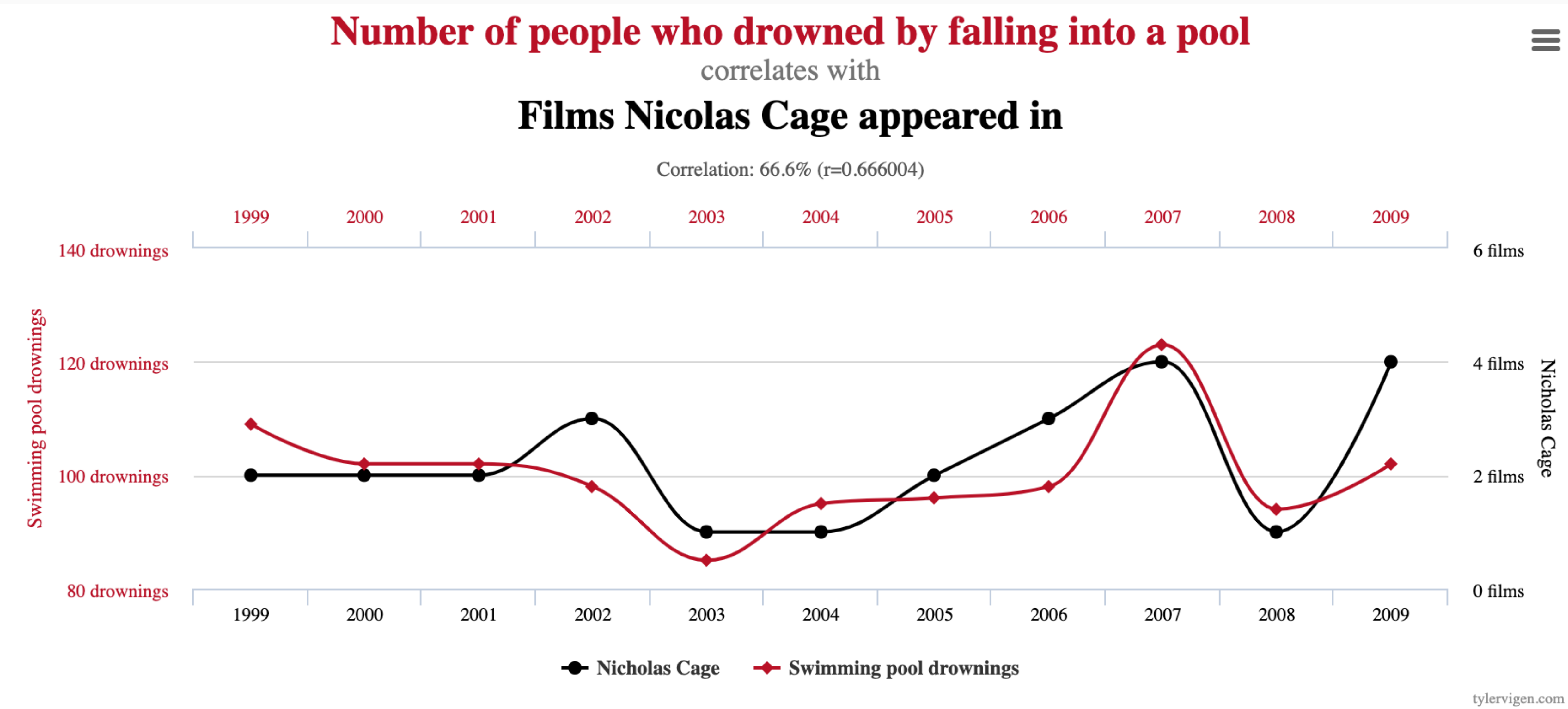
Let's Try it! Go to Colab using this link:
https://colab.research.google.com/drive/19cYkJ04-0toqKWvcI4DTy97JDh4w_F_Q?usp=sharing

To conclude . . .

1. Why do experiments work? (Potential outcomes model)
2. Experimental design and implementation
   - Within vs. between subject designs
   - Internal vs. external validity
     - Convenience samples
     - Confounders and randomization checks
   - Blocking
   - Breakout rooms: experimental designs
3. Conjoint experiments
   - Theory
   - Implementation: code

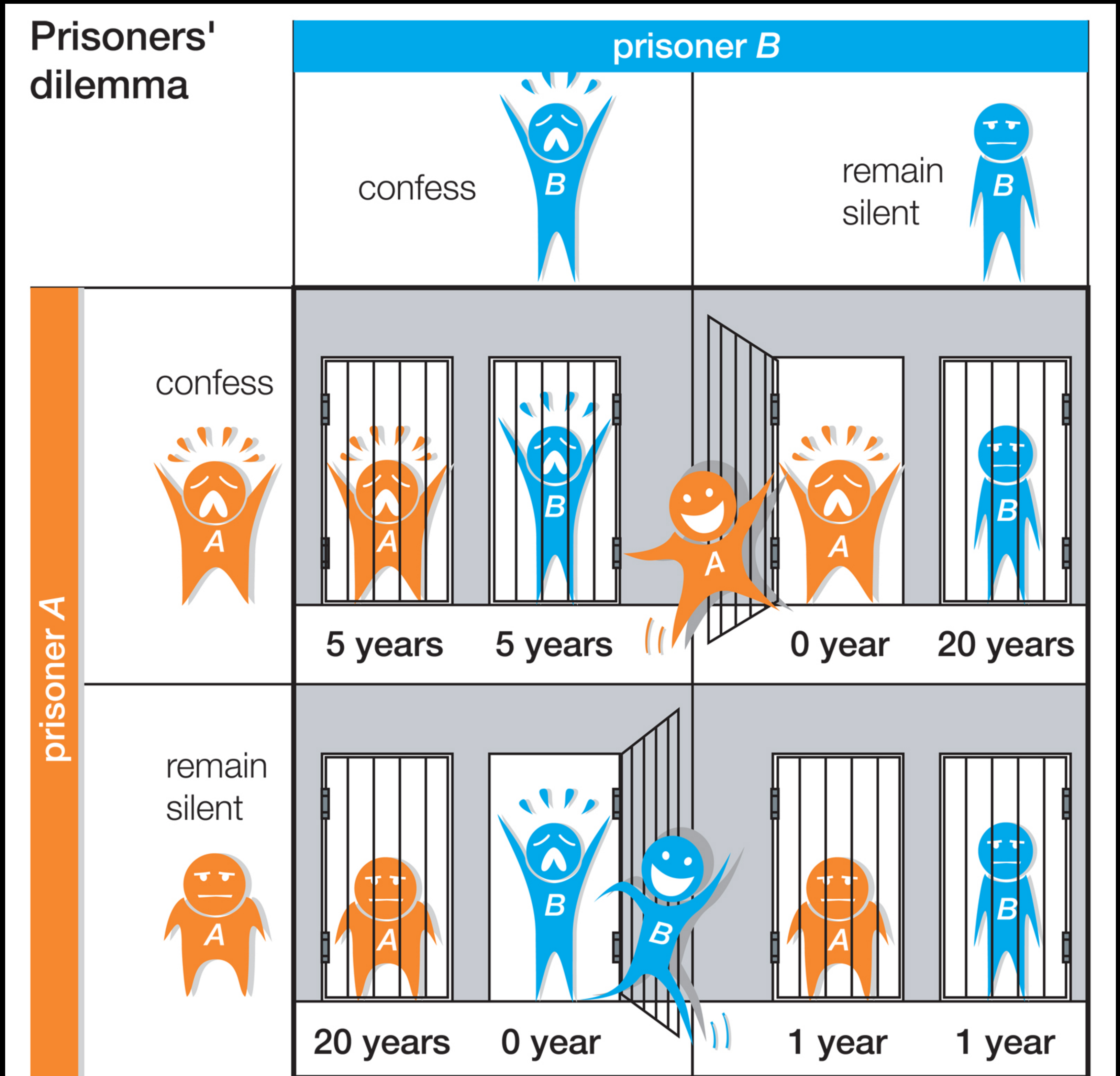
Experiments Are Not THE Answer

- But are AN answer
  - Allow us to get at causality better than observational studies
  - Need external validity



Data sources: Centers for Disease Control & Prevention and Internet Movie Database

On the other hand . . .



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What About Natural Experiments?

- Regression discontinuity (RD) designs = natural experiment
- Close elections
- Incumbency effects:
  - US: as expected — positive!
  - Klasnja and Titunik (2017)
    - Incumbency advantage in Brazil in 1996/2012: disadvantaged candidates
- RDs/natural experiments = specific to a time and place

Experiments Are Not THE Answer

- But are AN answer
  - Allow us to get at causality better than observational studies
  - Need external validity
- REPLICATION IS THE ANSWER
  - Randomization does not always give us equality between control and treatment groups one covariates
  - Every method has its downsides